Horizon 2020
European Union Funding
for Research & Innovation

Deliverable 2.4: *Report on environmentally sustainable, resilient forest models*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101037247

Project Acronym	SILVANUS
Grant Agreement number	101037247 (H2020-LC-GD-2020-3)
Project Full Title	Integrated Technological and Information Platform for Wildfire Management
Funding Scheme	IA – Innovation action

DELIVERABLE INFORMATION

Deliverable Number:	D2.4
Deliverable Name:	First report on environmentally sustainable, resilient forest models
Dissemination level:	PU
Type of Document:	R
Contractual date of delivery:	30/09/2022 (M24)
Date of submission:	03/11/2023 (M26), rev. 06/08/2024
Deliverable Leader:	AUA
Status:	Draft
Version number:	V1.0
WP Leader/ Task Leader:	TUZVO, AUA, CMCC, ASSET
Keywords:	Forest models, climate, forest resilience, wildfires
Abstract:	This document offers a comprehensive guide on tools, models, and software crucial for managing environmentally sustainable and resilient forests under increasing environmental changes and anthropogenic pressures. It includes an extensive range of topics such as fire behavior modeling, canopy fuel load, fire risk assessment, climate change impacts, wildfire ignition prediction, biodiversity, and forest management. Additionally, it covers air quality, human risk modeling, hydraulic models for soil erosion, and desertification indices. Aimed at researchers, policymakers, and forest management professionals, this deliverable combines theoretical and practical approaches to address the complex challenges of forest management, particularly in wildfire scenarios.

Lead Author(s):	Spyridon Kaloudis, Stavroula Galanopoulou, Dimitrios Raptis, Eudoxia Lykoudi, Konstantinos Demestichas, Dimitrios Sykas (AUA); Andrea Majlingova, Lenka Marcinekova (TUZVO); Monia Santini, Tammam Suliman (CMCC); Kusrini Kusrini, Arief Setyanto, Kumara Ari Yuwana, Gardyas Bidari Adninda, Fitria Nucifera, Renindya Azizza Kartikakirana (AMIKOM); George Sakkas (KEMEA); Panagiotis Oikonomou (UTH); Marek Gašparín (FRS MB); Igor Milić (UASVG)
Reviewers:	Krishna Chandramouli (VTG), Michele Corleto (PEGASO)

Disclaimer

Document History			
Version	**Date**	**Contributor(s)**	**Description**
V0.10	14/2/2022	AUA	Initial identification of forest models that are of relevance to SILVANUS
V0.20	3/3/2022	AUA	Explanation of the model inventory approach, proposed to be followed in WP2
V0.30	17/5/2022	AUA, ALL	Initial contributions on forest models and refinement of the inventory approach
V0.40	6/7/2022	ALL	Additional contributions on forest models
V0.50	20/9/2022	ALL	Additional contributions on forest models
V0.60	20/2/2023	AUA, ALL	Additional contributions and updates on forest models; refinement of the approach and timeplan
V0.70	8/6/2023	AUA	Proposed table of contents
V0.71	12/6/2023	AUA, ALL	Revision of table of contents
V0.80	21/9/2023	ALL	Partners’ contributions into the document
V0.90	14/10/2023	ALL	Final contributions to the deliverable
V0.95	24/10/2023	AUA	Integration and editing
V1.00	31/10/2023	AUA	Addressing of peer review comments and final check
V1.05	01/08/2024	AUA, TUZVO, KEMEA	Contributions to address the RP2 review comments
V1.10	06/08/2024	AUA	Revised version and final check

List of Contributors

Partner	Author(s)
AUA	Spyridon Kaloudis, Stavroula Galanopoulou, Dimitrios Raptis, Eudoxia Lykoudi, Konstantinos Demestichas, Dimitrios Sykas, Dimitrios Zografakis, Constantina Costopoulou
TUZVO	Andrea Majlingova, Lenka Marcinekova
CMCC	Monia Santini, Tammam Suliman
AMIKOM	Kusrini Kusrini, Arief Setyanto, Kumara Ari Yuwana, Gardyas Bidari Adninda, Fitria Nucifera, Renindya Azizza Kartikakirana
UASVG	Igor Milić
KEMEA	George Sakkas
ASSET	Giovanna Mangialardi, Marino Spilotros, Letizia Musaio Somma, Daniele Panarese
UTH	Panagiotis Oikonomou, Georgios Boulougaris, Konstantinos Kolomvatsos
FRS MB	Marek Gašparín
VTG	Tomas Piatrik

List of beneficiaries

No	Partner Name	Short name	Country
1	UNIVERSITA TELEMATICA PEGASO	PEGASO	Italy
2	ZANASI ALESSANDRO SRL	Z&P	Italy
3	INTRASOFT INTERNATIONAL SA	INTRA	Luxembourg
4	THALES	TRT	France
5	FINCONS SPA	FINC	Italy
6	ATOS IT SOLUTIONS AND SERVICES IBERIA SL	ATOS IT	Spain
6.1	ATOS SPAIN SA	ATOS SA	Spain
7	EMC INFORMATION SYSTEMS INTERNATIONAL	DELL	Ireland
8	SOFTWARE IMAGINATION & VISION SRL	SIMAVI	Romania
9	CNET CENTRE FOR NEW ENERGY TECHNOLOGIES SA	EDP	Portugal
10	ADP VALOR SERVICOS AMBIENTAIS SA	ADP	Portugal
11	TERRAPRIMA - SERVICOS AMBIENTAIS SOCIEDADE UNIPESSOAL LDA	TP	Portugal
12	3MON, s. r. o.	3MON	Slovakia
13	CATALINK LIMITED	CTL	Cyprus
14	SYNTHESIS CENTER FOR RESEARCH AND EDUCATION LIMITED	SYNC	Cyprus
15	EXPERT SYSTEM SPA	EAI	Italy
16	ITTI SP ZOO	ITTI	Poland
17	Venaka Treleaf GbR	VTG	Germany
18	MASSIVE DYNAMIC SWEDEN AB	MDS	Sweden
19	FONDAZIONE CENTRO EURO-MEDITERRANEOSUI CAMBIAMENTI CLIMATICI	CMCC F	Italy
20	EXUS SOFTWARE MONOPROSOPI ETAIRIA PERIORISMENIS EVTHINIS	EXUS	Greece
21	RINIGARD DOO ZA USLUGE	RINI	Croatia
22	Micro Digital d.o.o.	MD	Croatia
23	POLITECHNIKA WARSZAWSKA	WUT	Poland
24	HOEGSKOLAN I BORAS	HB	Sweden
25	GEOPONIKO PANEPISTIMION ATHINON	AUA	Greece
26	ETHNIKO KENTRO EREVNAS KAI TECHNOLOGIKIS ANAPTYXIS	CERTH	Greece
27	PANEPISTIMIO THESSALIAS	UTH	Greece
28	ASSOCIACAO DO INSTITUTO SUPERIOR TECNICO PARA A INVESTIGACAO E DESENVOLVIMENTO	IST	Portugal

No	Partner Name	Short name	Country
29	VELEUCILISTE VELIKA GORICA	UASVG	Croatia
30	USTAV INFORMATIKY, SLOVENSKA AKADEMIA VIED	UISAV	Slovakia
31	POMPIERS DE L'URGENCE INTERNATIONALE	PUI	France
32	THE MAIN SCHOOL OF FIRE SERVICE	SGPS	Poland
33	ASSET - Agenzia regionale Strategica per lo Sviluppo Ecosostenibile del Territorio	ASSET	Italy
34	LETS ITALIA srls	LETS	Italy
35	Parco Naturale Regionale di Tepilora	PNRT	Italy
36	FUNDATIA PENTRU SMURD	SMURD	Romania
37	Romanian Forestry Association - ASFOR	ASFOR	Romania
38	KENTRO MELETON ASFALEIAS	KEMEA	Greece
39	ELLINIKI OMADA DIASOSIS SOMATEIO	HRT	Greece
40	ARISTOTELIO PANEPISTIMIO THESSALONIKIS	AHEPA	Greece
41	Ospedale Israelitico	OIR	Italy
42	PERIFEREIA STEREAS ELLADAS	PSTE	Greece
43	HASICSKY ZACHRANNY SBOR MORAVSKOSLEZSKEHO KRAJE	FRB MSR	Czechia
44	Hrvatska vatrogasna zajednica	HVZ	Croatia
45	TECHNICKA UNIVERZITA VO ZVOLENE	TUZVO	Slovakia
46	Obcianske zdruzenie Plamen Badin	PLAMEN	Slovakia
47	Yayasan AMIKOM Yogyakarta	AMIKOM	Indonesia
48	COMMONWEALTH SCIENTIFIC AND INDUSTRIAL RESEARCH ORGANISATION	CSIRO	Australia
50	FUNDACAO COORDENACAO DE PROJETOS PESQUISAS E ESTUDOS TECNOLOGICOS COPPETEC	COPPETEC	Brazil

Table of Contents

Index of figures

Index of tables

Executive Summary

The primary objective of this deliverable is to elucidate the models and tools employed in managing environmentally sustainable and resilient forests, especially in the face of increasing environmental changes and anthropogenic pressures. The increasing importance of understanding and managing forests, especially considering the heightened challenges posed by wildfires, is emphasized. The SILVANUS Knowledge Hub (contained in Chapter 2) offers an exhaustive inventory of forest models, covering aspects from fire behavior, canopy fuel load estimation, fire risk assessment, to the impacts of climate change on forests. It also delves into models related to air quality, evacuation needs, soil erosion, and desertification indices.

More specifically, this deliverable deals with the following categories of forest models:

- Fire Suppression & Resource Deployment (M11): A deep dive into strategies and methodologies for resource deployment, emphasizing the increasing challenges posed by wildfires and the necessity for optimizing resources and strategies.
- Wildfire Behavior & Modeling (M21): An in-depth exploration of the complexities of modeling wildfire behaviors, discussing different categories of models and their applications.
- Canopy Fuel Load Estimation (M22): Emphasizing the pivotal role of understanding canopy fuel load for modeling crown fire behaviors.
- Fire Risk Assessment & Damage Estimation (M23): Comprehensive understanding of wildfire risk assessment, including the synthesis of hazard, exposure, and vulnerability dimensions.
- Climate Change Impact on Forests (M41): Delving into how climate change directly and indirectly influences forests and the importance of adaptive forest management.
- Predicting wildfire ignition (M51): A collection of various models that have been used to study and predict wildfire ignitions, incorporating diverse techniques, such as logistic regression, neural networks, L-functions, $\chi 2$ analysis, kernel estimation, Bayesian statistics, spatial autoregressive models, Maximum Entropy algorithms, and back-propagation neural networks.
- Forest management and biodiversity (M61-M62): This highlights the importance of managing environmental and forest factors to mitigate fire risks, categorizing them as Biotic and Abiotic, with the mosaic model aiding in targeted forest management. Also, the models focus on the nuances of measuring biodiversity, emphasizing its complexity beyond mere species count, and introduces methodologies for biodiversity indexing and ecological site classification, while discussing the intricate management of forest and landscape projects, emphasizing sustainable practices and the necessity of landscape-level tools and models for effective forest evolution and management.
- Air quality and human risk modelling (M71-M72): These categories model the environmental and health impacts of wildfires on air quality, detailing the pollutants released and their associated health risks, while also highlighting models and tools developed to estimate emissions and predict smoke dispersion. The group of models focused on supporting evacuation needs stresses the importance of effective evacuation planning, especially in wildfire-prone areas, outlining the key components of a proactive management model and the use of tools like the SRUUK system for timely alerts to citizens.
- Soil erosion and hydraulics models and indices (M82-M84): An analysis of models employed for estimating soil loss, sediment transfer, and deposition at various scales. They also include various hydraulic models and indices, focusing on soil erosion, water flow, and sediment transport.
- Soil Quality & Desertification Indices (M85-M86): Evaluating soil health, contamination levels, and challenges posed by desertification, highlighting the importance of cohesive strategies.

This deliverable serves as a holistic guide, addressing the multifaceted challenges associated with forest management, especially concerning wildfires. It is an indispensable resource for researchers, policymakers, and professionals in forest management, offering both theoretical and hands-on perspectives on the subject.

1. Introduction

This deliverable aims at describing and assessing the models and tools that are used in managing environmentally sustainable and resilient forests. In an age marked by rapid environmental changes and increasing anthropogenic pressures on natural landscapes, understanding, and managing our forests has become more critical than ever. This deliverable is a comprehensive guide that aims to address the multifaceted challenges associated with forest management, particularly in the context of wildfires.

Chapter 2 unveils the “SILVANUS Knowledge Hub”, an extensive inventory of forest models. This chapter is subdivided into numerous sections, each detailing a specific model or methodology related to forest management and wildfire prediction. From understanding fire behavior, canopy fuel load estimation, and fire risk assessment, to delving into the effects of climate change on forests and predicting wildfire ignition, the SILVANUS Knowledge Hub offers a holistic approach to modern forest management. Further, it explores models that estimate air quality during fires, support evacuation needs during fire events, and even models that gauge the impact of wildfires on climate. Additionally, there are sections dedicated to soil erosion, hydraulics, soil quality, and desertification indices, showcasing the breadth and depth of the knowledge hub.

More specifically, chapter 2.1 outlines the methodology followed for the conducted research review. Then, the other sections of Chapter 2 serve as a comprehensive inventory of forest models that are of relevance to a comprehensive integrated forest management platform such as the one offered by SILVANUS. The following paragraphs provide an overview of the various categories of models that are analyzed across these sections.

The “M11: Strategies and methodologies for resource deployment and management tactics” section discusses that the increasing frequency and severity of wildfires pose significant threats to human lives, ecosystems, and infrastructure. This section delves into the strategies and methodologies for resource deployment and management tactics in fire suppression. Fire suppression activities span from preparedness, where resources are deployed, to the response phase of managing an active wildfire. Multiple factors, including human activities and global warming, contribute to the rising occurrence of wildfires. With growing fire suppression costs and challenges in efficient resource allocation, there’s a pressing need for optimizing resources and strategies. Operations research offers tools for decision-makers, providing an integrated approach to tackle the complexities of fire management. The section also highlights the importance of fire growth simulation models, risk maps, and geographic information systems in strategizing fire suppression. The review incorporates various literature sources from prominent databases to provide a comprehensive understanding of the current models and tools in wildfire management.

The “M21: Fire behavior models” section delves into the complexities of modeling wildfire behaviors. The unpredictability of wildfires has led to the development of various simulation models to study and prevent them. These models face challenges due to intricate physics and chemistry interactions, computational demands, and defining input parameters. Wildfires are multifaceted, involving chaotic chemical reactions and physical processes spanning varying scales. A critical component in studying wildfires is the rate of spread (ROS), influenced by factors like fuel type, terrain, and atmospheric conditions. Three primary model categories for wildfire spread are: physical and quasi-physical models, empirical and quasi-empirical models, and simulation and mathematical analog models. The recent trend in wildfire modeling combines both physical and empirical fire models with computational fluid dynamic (CFD) models. Two main types of models simulate dynamic spatial fire spread: models based on CFD principles and fire perimeter propagation models. Additionally, mathematical models and geographic information systems (GIS) play a pivotal role in analyzing wildfire data, aiding in the creation of software simulations for fire spread in varying terrains and environments. The research overview incorporates literature from prominent databases, using specific keywords to ensure relevance to the study of wildfire behavior and modeling.

The “M22: Models for canopy fuel load estimation" section emphasizes the importance of understanding canopy fuel load (CFL) when modeling crown fire behaviors. CFL, given in kg per m^2, is critical for predicting the heat released during fires and calculating canopy bulk density (CBD). Canopy fuel load refers to the canopy fuel mass per unit ground area, with only a segment of it being consumed during wildfires, typically the thinnest parts like foliage and branches. Different researchers have varying definitions for what constitutes available CFL, with some focusing solely on conifer needles, while others include a broader range of needles and branches. The canopy fuel load can be measured at both tree and stand levels, though for fire modeling, stand-level measurements are more pertinent. To estimate CFL without destroying trees, allometric models are used. These models, often based on Ordinary Least Squares (OLS) theory, employ mathematical transformations to provide reliable estimates. Some research also utilizes weighted nonlinear regression as an alternative approach.

The “M23: Models, methodologies, and indices for fire risk assessment and fire damage estimation” section, based upon the work by Chuvieco et al. (2023), delineates wildfire risk assessment as a synthesis of three core dimensions: hazard, exposure, and vulnerability. In the context of wildfires, "fire risk" refers to the likelihood and potential impact of a wildfire in a specific location and time, while "hazard" pertains to factors that can either trigger or amplify a wildfire. Vulnerability encompasses susceptibility to damage and limited recovery or adaptability. Fire risk assessment aims to estimate the probability, spread, affected areas, and potential damages of a wildfire. Key influencing factors include weather conditions, topography, available fuels (which can be altered by human interventions), human presence (related to ignition probability and vulnerability), ecosystem services and ecological values, and resilience (an ecosystem’s capacity to endure and rebound from fire impacts).

The “M24: Models of surface fuel load” section discusses the three general types of wildland fires: ground fires, surface fires, and crown fires. Among these, surface fires are the most common and consume fuels present between the ground and canopy. Key attributes of these fires include their spread rate, flame length, and fireline intensity. Predicting the spread rate is crucial for fire management as it indicates fire severity. The most prevalent model for predicting this rate is the semi-empirical model proposed by Rothermel (1972), incorporated into several fire modelling systems. This model, adapted from Frandsen’s heat balance model and various experiments, utilizes an equation to calculate the rate of spread based on several factors, including reaction intensity, wind speed, slope steepness, and fuelbed bulk density. To operationalize this model, inputs from both fuel properties and environmental values are necessary.

The “M31: Predicting future Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) using Stand Basal Area Increment” section emphasizes the importance of predicting changes in CFL and CBD for crown fire behavior modeling. These variables help quantify potential crown fire risks and guide silvicultural treatments to manage fuel availability. Predicting CFL and CBD changes over time is complex due to many varying factors. In the absence of specialized software or allometric equations, indirect methods are essential. Currently, CFL and CBD estimations rely on allometric relationships that integrate tree diameter or basal area. By connecting these equations with forest growth models, one can anticipate changes in crown fuel properties. These growth models fall into three categories: empirical, progress-based, and hybrid. Empirical models, developed from extensive field datasets, are most common, predicting tree growth rate based on factors like age, soil fertility, and competition. While these models offer consistency across various forest ecosystems, they may not capture the entire complexity of ecological processes. The proposed combination of crown fuel and growth models provides a temporary solution, but it may lead to marginal predictions due to potential inconsistencies.

The “M41: Models for climate change impact on forests” section discusses how climate change affects forests both directly, through changes in CO2, temperature, and precipitation, and indirectly through disturbances like fires and diseases. These alterations influence vital forest processes like photosynthesis, growth, and mortality. Regional variations exist in forest responses to climate change; some regions experience enhanced growth, while others face declines. Given the multifaceted nature of these shifts, forest managers must adapt their strategies for sustainable management, ensuring ecosystem service provision. They employ various scientific tools, including growth models, to aid decision-making. These models represent forest dynamics and vary in complexity. While traditional models are empirical, based on inventory data, modern ones are process-based, simulating physiological processes and their relation to environmental conditions. Hybrid models merge features of both, always factoring in climatic conditions.

The “M42: Models for calculation of local weather conditions” section highlights that national meteorological agencies base their forecasts on global meteorological models, which are then refined for regional or national scales using local data. While global models can predict weather up to 15 days or even a month, accuracy diminishes over extended periods. Key global forecast models include the Global Forecast System (GFS), European Center for Medium-Range Weather Forecast (ECMWF/CEP), Global Environmental Multi-scale model (GEM), UK Meteorological Office (UKMO), Japanese Meteorological Agency (JMA), Icosahedral Nonhydrostatic Weather and Climate Model (ICON GLOBAL), and NASA/GEOS5. National agencies enhance these models using data from local weather stations, thereby improving forecast precision on a localized scale.

The “M43: Models for estimating the effect of environmental factors on forest susceptibility to fire” section places emphasis on two models identified in “M41: Models for climate change impact on forests”, namely TREEMIG and CENTURY v4.0. TREEMIG predicts tree species migration based on climate, seed dispersal, and competition, but it simplifies species interactions and ignores genetic variability's influence on adaptability. CENTURY v4.0 is a process-based model that focuses on carbon and nitrogen dynamics, analyzing ecosystem functionality and the impacts of management. Despite its comprehensive approach, it requires substantial computational power and may not account for all environmental factors, limiting its application to specific ecosystems and management practices.

With regards to the “M51: Models/Knowledge/Indices for predicting wildfire ignition” section, wildfire ignition prediction is recognized as a pivotal component of wildfire behavior modeling. The goal is to forecast potential fire starts spatially, enabling efficient resource allocation and early fire detection for suppression. Although prior modeling has concentrated on wildfire spread rates, predicting ignition probabilities can enhance firefighting efforts. Wildfire ignition risks refer to the likelihood of a fire starting in specific conditions in a given area. Ignitions primarily fall into two categories: naturally-caused and human-caused, with the latter being more prevalent. Key factors influencing ignition include fuel characteristics (type, load, composition, and moisture), weather conditions (temperature, humidity, and wind speed), topography (solar radiation exposure and altitude), and human presence (negligence and potential arson). Numerous models have been developed to predict these ignitions, employing techniques like the Analytical Hierarchy Process, Artificial Neural Networks, logistic regression, Maximum Entropy, Bayesian statistics, and more, often integrated with Geographic Information Systems for spatial analysis. These models consider various variables, from environmental to human factors, to forecast ignition probabilities, aiding in wildfire management strategies.

The “M61: Enhancement of fire risk resilience through forest management” section emphasizes the importance of understanding and managing environmental and forest (EF) factors to reduce forest fire risks. These factors, which affect the forest’s structure and resistance to fires, are classified based on their origin into Biotic and Abiotic categories. Biotic factors include elements from the organic world, like flora, fauna, and human activities. Abiotic factors derive from the inorganic world, encompassing climate, soil, and landscape elements. The mosaic model of geographical representation is highlighted for its ability to provide a focused approach to forest management, facilitating a strategic response to high-risk areas, optimizing forest productivity, and ensuring cost-effective treatments. The section classifies the factors further, detailing specific components under each category, such as species structure, wind speed, soil depth, and altitude.

The “M62: Models of biodiversity index and ecological site classification" section underscores the complexity and significance of measuring biodiversity. Biodiversity encompasses the variation of life at genetic, species, and functional trait levels, with indicators such as richness, evenness, and heterogeneity. While it is tempting to equate biodiversity with species richness, this perspective is simplistic and misleading. Biodiversity is not just about quantity; the identity and quality of species matter. Fragmentation or introduction of non-native species can lead to homogenization, reducing the distinctiveness of an ecosystem. Accurate quantification of biodiversity remains a challenge despite various tools and methods, such as counting species, using Shannon's diversity index, and employing emergy methods. An ecological site integrates various factors like climate, soil, and hydrology to describe an area's ecological potential. The section also provides an overview of methodologies and tools employed for biodiversity indexing and ecological site classification, drawing from extensive databases and research sources.

The "M63: Models for development of the forest and landscape management" section emphasizes the intricacies of managing vast forest and landscape projects, both for governments and private landowners. Traditional logging operations, focusing on profit, often overlook the broader sustainable context, leading to a societal shift towards ecologically sustainable products. Consequently, forest managers now contemplate multi-objective criteria encompassing environmental and socio-ecological aspects. Landscape-level approaches are increasingly relevant for forest sustainability and land-use planning, addressing the heterogeneity and dynamic nature of forests. Various indicators, spanning economic, social, and ecological components, are essential for sustainability monitoring, prompting the need for landscape-level tools. The increasing demand for landscape foresight studies and the prominence of forests in many landscapes necessitate effective tools to model landscape evolution over time. Landscape modeling and optimization offer potential advancements in timber production, while species or clone selection within specific sites enhances management efficiency. The selection process focused on gathering literature from renowned databases using a comprehensive set of keywords.

The "M71: Models and/or indices that estimate air quality during the fire and risk for human health" section highlights the environmental and health hazards posed by wildfires. Such fires release various pollutants that can adversely affect air quality and pose health risks to firefighters, local residents, and distant populations depending on wind direction. These emissions consist of a mixture of gases, particulates, and compounds, with primary pollutants including PM2.5, carbon monoxide, oxides of nitrogen, sulfur dioxide, and volatile organic compounds. These compounds also contribute to the creation of PM2.5 and ozone. Health risks from wildfire exposure vary based on the toxicity of emitted substances, exposure characteristics, and the vulnerability of exposed individuals. Numerous studies link wildfire smoke exposure to respiratory ailments, cardiovascular issues, adverse birth outcomes, mental health disorders, and even death. Current research focuses on understanding the effects of wildfire smoke on air quality, leading to the development of numerous models, indices, and tools to estimate emissions and predict smoke dispersion.

The "M72: Models for estimating air quality and corresponding risk for human health during forest fires" section emphasizes the critical nature of effective evacuation planning, especially in areas like the Croatian coast which are prone to wildfires during the summer months, posing risks to both residents and tourists. Evacuation is a crucial civil protection measure, ensuring the safety of citizens when wildfire threats loom. Several considerations guide the evacuation process, including the primary objective of safeguarding citizens, developing early warning systems, and raising public awareness through education. A proactive management model is proposed, consisting of Planning, Early Warning Systems, as well as Training and Exercises. Planning involves identifying evacuation routes, safe locations, communicating the evacuation plan, and ensuring all stakeholders are familiar with it. Early warning systems, vital for timely evacuations, could incorporate smoke detection sensors, heat sensors, weather monitoring, surveillance cameras, and mobile applications. Regular training and exercises are essential to familiarize operational forces and the public with evacuation procedures. The SRUUK system, implemented at the Republic of Croatia's level, serves as a vital tool for alerting citizens about crisis situations, supplementing traditional siren alarms. Through SRUUK, warnings and instructions are sent directly to mobile devices in the affected area, ensuring timely and informed actions in crisis situations.

The "M82: Models for soil erosion" section delves into the critical environmental challenge of soil erosion, which results from a combination of natural and human-induced activities. These erosions manifest as landforms created by varying driving forces, including overland flow, fluvial processes, landslides, wind, coastal actions, and glacial movements. Factors like climate variability and land degradation exacerbate the erosion problem. It's vital to note that soil erosion threatens long-term soil sustainability, necessitating proactive soil conservation measures. One of the primary tools for understanding and addressing soil erosion is the integration of Geospatial Information Science (GISc)-based analysis with modeling. This combination facilitates the prediction and understanding of erosion, aiming to mitigate its adverse effects. The modeling of erosion offers a systematic approach to estimate soil erosion under diverse conditions. The growth of geographic information systems (GIS) and the adoption of remote sensing data have significantly boosted erosion model development. Although numerous erosion models exist, choosing the right one for specific applications remains a challenge. At their core, these models employ mathematical relationships to replicate the primary erosion processes. Generally, these models are categorized into empirical models, conceptual models, and physically-based models.

The “M83: Geomorphological and topographic models for sediment yield and discharge” section focuses on various models and indices related to hydraulics and geomorphology. Notably, model M83.1, the Dendy Bolton formula, is used to determine sediment yield from multiple types of erosion by using watershed area and basin runoff data. M83.2, by Avendaño Salas et al., offers a database with mean annual sedimentation rates for Spanish reservoirs, spanning multiple regions but excluding the humid Northwestern area. M83.3, an equation by Lu et al., was formulated using sediment discharge data from the Upper Yangtze basin in China. M83.4, developed by Webb and Griffiths, provides an equation for estimating annual sediment discharge based on data from catchments in northern Arizona. M83.5, by Mulder and Syvitski, offers insights into predicting the frequency of hyperpycnal plumes from river discharge based on rating curve characteristics. M83.6, Geomorphological models, correlate the suspended sediment yield with geological and morphological parameters, focusing on geomorphologic parameters which are seldom used in international research. However, these models fall short in pinpointing high-risk erosion areas, as the parameters used don't provide spatial distribution.

The “M84: Soil erosion models focused on hydraulics” section presents various hydraulic models and indices. Notably, M84.1 is the Revised Morgan-Morgan-Finney (RMMF) model which divides soil erosion into water and sediment phases, focusing on rainfall energy and runoff volume. M84.2, based on physically-based indices, introduces the broken line smoothing Q-Qs as an alternative to the ordinary single rating curve, emphasizing the influence of sediment motion threshold. The section also describes Composite Models (CM) that blend different modeling approaches. Notable models include the ANSWERS model (M84CM.1), designed for catchment erosion assessment; the AGWA tool (M84CM.2) for hydrologic impact assessment; the CREAMS model (M84CM.3) which predicts runoff, erosion, and chemical transport; the GUEST program (M84CM.4) for erosion analysis; the EPIC model (M84CM.5) for U.S. soil erosion-productivity relations; the WEPP model (M84CM.6) for detailed erosion prediction; the AGNPS model (M84CM.7) for nonpoint source pollutant prediction; the IHACRES-WQ model (M84CM.8) for rainfall-runoff; the LISEM model (M84CM.9) for hydrological and soil erosion predictions; the SWAT model (M84CM.10) which focuses on the viability of lumping parameters at different scales; and the SWRRB model (M84CM.11), simulating hydrologic processes in rural basins. These models offer insights into various aspects of hydraulics, from erosion to sediment transport and hydrological impacts.

The “M85: Soil quality indices” section delves into methods and models for evaluating soil quality. Soil quality is defined as a soil's ability to function within its ecosystem, and its assessment is multifaceted, considering physical, chemical, and biological aspects of soil. While various factors, including climate and topography, influence soil properties, baseline values are essential for evaluating soil quality. Typical soil quality assessments focus on physical and chemical characteristics, but recent studies have emphasized the importance of biological and biochemical indicators. The section highlights several soil quality and pollution indices. Among them are the Soil Quality Index (SQI) for forest soil quality monitoring, the Geoaccumulation Index (Igeo) for assessing heavy metal contamination, and the Single Pollution Index (PI) for evaluating individual heavy metal threats. Other indices, like the Enrichment Factor (EF) and Contamination Factor (Cf), determine heavy metal origins and soil contamination, respectively. Additionally, more comprehensive indices, such as the Pollution Load Index (PLI) and Nemerow Index (PINemerow), provide overarching evaluations of soil contamination and quality. These models and indices offer tools for understanding soil health, contamination levels, and potential environmental impacts.

The “M86: Desertification indices” section discusses the challenges and threats posed by desertification, particularly within the EU. As noted in a special report by the EU, the risk of desertification isn't being adequately addressed, and there's an absence of a cohesive strategy to achieve land degradation neutrality by 2030. Desertification, as defined by the UNCCD, is land degradation in specific climate zones due to factors like climate variations and human activities. While the Aridity Index (AI) is traditionally used to measure desertification, its accuracy is debated, especially in the current context of rising CO2 levels. Factors like changing precipitation patterns and soil moisture levels can be indicators of desertification, but they may not provide a clear forecast for future changes in land conditions. Both natural environmental factors and human-induced activities play roles in exacerbating desertification. The issue is recognized globally and is a focus of the UN's 15th Sustainable Development Goal, which aims to protect terrestrial ecosystems and combat desertification.

Together, these sections provide a comprehensive overview of both the theoretical and practical aspects of forest management in the context of wildfires, serving as an invaluable resource for researchers, policymakers, and forest management professionals alike. A summary and conclusions, based on the conducted analysis, is provided in chapter 3.

2. The SILVANUS Knowledge Hub - Inventory of forest models

2.1 Context and approach

From the beginning of the project, the SILVANUS team working in WP2 ("Environmentally sustainable, resilient forest models and assessment framework") outlined a solid and comprehensive approach for conducting its work. This approach evolved around the creation and establishment of a Knowledge Hub, which would contain an inventory of forest models and tools that are of relevance for a comprehensive and feature-rich integrated forest management platform, such as the one being developed and tested by SILVANUS.

In the context of the present document, a **model** is a theoretical or computational framework that represents, simulates, or predicts real-world processes or phenomena. In the context of forest management and forest wildfires, models typically involve mathematical equations, algorithms, or simulations that aim to understand or forecast events such as fire spread, fuel dynamics, and ecological changes. A **tool**, on the other hand, is an application or software that utilizes one or more models to perform specific tasks or analyses. Tools often provide user-friendly interfaces and practical functionalities that allow users to apply models to real-world scenarios. They may also include additional features like data visualization, user inputs, and interactive simulations. From the above, it becomes apparent that a tool might implement or integrate one or several models, whereas a model can be implemented in none, one or several tools (many-to-many relationship).

In previous work of the SILVANUS project under WP2, deliverable D2.1 "Report on existing sustainable forest management services" provided the opportunity to establish and clarify a common vocabulary and terminology, especially considering that the term "forest models" can have a very general and multi-faceted meaning. Then, deliverable D2.2 "First report on environmentally sustainable, resilient forest models" outlined the concrete methodology (inventory-based approach) to be followed for collecting, compiling and analyzing information on relevant forest models and tools.

Following this methodological framework, SILVANUS partners, in the context of WP2, conducted research and review activities to contribute into the Knowledge Hub. In particular, deliverable D2.2 defined the following list of model categories as in-scope and of interest to SILVANUS:

- Strategies/methodologies for resource deployment and management tactics
- Fire behavior models
- Models for Canopy fuel load estimation
- Models, methodologies and indices for fire risk assessment and fire damage estimation
- Models of surface fuel load
- Forest stand models that represent and predict forest stand structure and its characteristics through time, especially those that calculate stand basal area and individual tree diameter
- Models for climate change impact on forests, especially those of forest management adaptation to climate change impact on forests
- Models for calculation of local weather conditions, especially those that calculate air velocity and direction according to local topography
- Models to estimate the effect of environmental factors on forest susceptibility to fire
- Models/Knowledge/Indices for predicting wildfire ignition
- Models/Knowledge/Indices for wildfire prevention, where areas at high risk of wildfire can be treated and protected from ignitions throughout the peak fire season, i.e. forest management practices to prevent ignition and reduce fire dynamic
- Models/Indices of biodiversity index and ecological site classification
- Models for ecosystem development and forest growth
- Models/Knowledge/Indices for development of the forest and landscape management alternatives for fire forest resilience and mitigation of fire impact (soil protection, flood reduction) for specific regions considering the information on biodiversity index and ecological site classification

- Models and/or indices that estimate air quality during the fire and risk for human health
- Models/methodologies to simulate and support evacuation needs due to fire event
- Models/indices for soil erosion
- Models/indices related to hydraulics (e.g., runoff, supply-stereo supply curves (Q-Qs curves), sediment discharge rating curves)
- Hydrogeological models (infiltration, percolation or filtration, etc.)
- Geomorphological - Topographic models/indices
- Soil quality Indices (e.g., soil texture, total carbon, organic matter, pH, nutrients, pollutants)
- Desertification indices
- Models/indices for wildfire impact on climate

As may be observed, already from the initial phase of the project, the decision has been to conduct, in the context of WP2, **a broad investigation** of existing and emerging forest-related models and tools, with a view to **1)** studying and analyzing models and tools that are of direct or indirect relevance to forming, protecting and maintaining environmentally sustainable forests, under the light of integrated forest management; and **2)** covering and consolidating in a common Hub a representative set of forest models and tools that will help accelerate research and innovation.

This is important because forests are complex and dynamic ecosystems that interact with various environmental factors, such as climate, soil, water, air, and human activities. Effective forest management requires a holistic understanding of these interactions to enhance forest resilience and sustainability, particularly concerning fire risk. Hence, the scope of this deliverable focuses on forest resilience in the context of fire risk. As such, while some models may not directly pertain to the forest structure itself, they are integral to the broader ecosystem dynamics that influence forest health and management.

For instance, models related to fire risk included in this deliverable are vital for assessing fire risk levels in both spatial and temporal dimensions. They guide the type and intensity of management interventions needed to improve forest resilience to fire. Fire risk is a significant component of the SILVANUS project, as understanding and mitigating this risk is crucial for protecting both forest ecosystems and the surrounding communities.

The broader category of soil models, which encompasses soil erosion, hydraulics, soil quality, and desertification indices, addresses a major component of forest ecosystems. Soil health and integrity are critical not only to forest resilience but also to overall forest sustainability. Soil conditions can be significantly affected by interventions aimed at increasing forest resilience and are also heavily impacted by fires, which can lead to increased erosion, flooding, and pollution. Understanding these soil dynamics is essential for developing effective conservation practices and ensuring long-term forest sustainability.

Models related to air quality and human risk are equally important, as they contribute to the preparedness and planning of local communities' safety measures. These models provide crucial information on the severity of potential fire events and help determine the necessary interventions in forests to minimize adverse effects. This includes the construction of fuel breaks and rescue roads, particularly in Wildland-Urban Interface (WUI) areas. These models ensure public safety and help planners design effective evacuation and intervention strategies.

Considering these interrelations, the inclusion of these model categories in this deliverable aligns with the SILVANUS project's goals of reducing and mitigating fire risk. Each model category plays a pivotal role in enhancing forest resilience and sustainability, making them essential components of the D2.4 inventory. This integrated perspective is essential for developing effective strategies to manage and protect forest ecosystems in the face of increasing environmental challenges.

From this initial strategic perspective, WP2 research and review activities started to be carried out in order to establish their first results as well as to continuously expand and enrich them. The work conducted in this period, until the submission of the present deliverable D2.4, has resulted in covering a wide series of forest models and tools, which cover almost of the initially identified categories. More specifically, the categories that are covered by SILVANUS in deliverable D2.4 are:

- M11: Strategies and methodologies for resource deployment and management tactics (presented in chapter 2.2)
- M21: Fire behavior models (presented in chapter 2.3)
- M22: Models for canopy fuel load estimation (presented in chapter 2.4)
- M23: Models, methodologies and indices for fire risk assessment and fire damage estimation (presented in chapter 2.5)
- M24: Models of surface fuel load (presented in chapter 2.6)
- M31: Models for predicting future Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) using Stand Basal Area Increment (presented in chapter 2.7)
- M41: Models for climate change impact on forests (presented in chapter 2.8)
- M42: Models for calculation of local weather conditions (presented in chapter 2.9)
- M43: Models for estimating the effect of environmental factors on forest susceptibility to fire (presented in chapter 2.10)
- M51: Models for wildfire ignition prediction (presented in chapter 2.11)
- M61: Enhancement of forest resilience through forest management treatments (presented in chapter 2.12)
- M62: Models of biodiversity index and ecological site classification (presented in chapter 2.13)
- M63: Models for the development of forest and landscape management (presented in chapter 2.14)
- M71: Models for estimating air quality and corresponding risk for human health during forest fires (presented in chapter 2.15)
- M72: Models to simulate and support evacuation needs due to forest fire event (presented in chapter 2.16)
- M82: Models for soil erosion (presented in chapter 2.17)
- M83: Geomorphological and topographic models for sediment yield and discharge (presented in chapter 2.18)
- M84: Soil erosion models focused on hydraulics (presented in chapter 2.19)
- M85: Soil quality indices (presented in chapter 2.20)
- M86: Desertification indices (presented in chapter 2.21)

Consequently, the majority of categories initially foreseen in D2.2 have been covered, either in standalone mode or as part of other categories (especially climate models and soil erosion models were reorganized).

As may be observed, to facilitate quick reference, a unique two-digit code has been assigned to each category of models in the following form: **M**XY, where X and Y are the two digits. All model categories are to some degree associated or linked to each other, but, in this reference scheme, model categories that share the first same digit are typically more closely related.

For each model category, research efforts were devoted to the following:

1. Research and identification of relevant models and tools for that category, through a survey of the relevant literature.
2. Where feasible, assessment of models and tools (according to the criteria presented in D2.2 and included also herein).
3. High-level description of the models and tools.
4. Where possible, more detailed description of either all or at least a selection of most promising models and tools, placing emphasis (where applicable) on the models' input/output variables, key mathematical equations or expressions, etc.

This work was supported by a Knowledge Hub established in a dedicated folder on the project's MS Teams repository. In particular, the goal for the SILVANUS Knowledge Hub has been to serve as a one-stop-shop for models and tools relevant to the categories defined above. Apart from collecting descriptions and key reference material of the models and tools, the Knowledge Hub featured two template files (tables) that had to be used: one for the metadata of the identified model or tool and one for the assessment of the identified model or tool.

Hence, for the harmonized description of the models, the attributes (columns) of two tables, i.e. "Model Metadata" and "Model Assessment", had to be filled in. These attributes and their meaning are presented below:

- <u>**Model Metadata**</u>
  - **Model Code** – *Assign a unique reference code for the identification of the model, in the form of MXY.Z, where XY is the unique code representing the model's category and Z is a unique number or string uniquely identifying the model within this category*
  - **Model Name or Title** – *Specify the name or title of the model, as most commonly used in the existing literature*
  - **Nature of Model** – *Specify: Mathematical, Non-mathematical (e.g., Knowledge, Processes), Index/Indices, Other*
  - **Applicability in Phases** – *Specify: A, B, C, or combinations. As a reminder: the three fire management phases are defined as follows (CORDIS 2023): A) Prevention and Preparedness; B) Detection and Response; and C) Restoration and Adaptation*
  - **Main Capabilities of the Model** – *Specify keywords (free selection) with main capabilities or features of the model*
  - **Main Restrictions of the Model** – *Comments on main limitations of the model, e.g., regarding the accuracy of measurements, the prediction of the values of variables, etc.*
  - **Implemented in S/W Products or Tools** – *Specify any existing S/W products or tools where this model is implemented*
  - **Additional Comments** – *Include any additional comments, if necessary*
  - **Main Reference(s)** – *Specify the main references (literature or other sources) that describe or review this model - Store these papers into the Knowledge Base, if possible in a dedicated folder, e.g. named MXY.Z folder*
- <u>**Model Assessment (with scores in specific criteria)**</u>
  - **Suitability and Completeness** - *Degree to which the model provides functions that meet user needs (when used under specified conditions), as well as degree to which the set of functions covers all user objectives in specific operational scenarios. Include a single integer score from 0 to 10. Convention:*
    Excellent (8-10)
    Satisfactory (6-8)
    Moderate (4-6)
    Inadequate (2-4)
    Unacceptable (0-2)

    Then, specify the weight (importance) for Suitability and Completeness as criterion for the assessment
  - **Prediction Capacity** - *Specify the prediction capacity (e.g., relevance, accuracy, or other suitable metric) as a percentage from 0 to 100% (the higher the better). Estimate an average value from the evidence that exists in literature reviews and papers*

    Then, specify the weight (importance) for Prediction Capacity as criterion for the assessment
  - **Data Requirements** - *Perform an assessment of the data requirements of the model. Higher data requirements (more data or more parameters) should yield lower scores. Convention - Data requirements are:*
    Few and very realistic (8-10)
    Moderate but generally realistic (6-8)
    Many but could be achieved under certain conditions (4-6)
    Very high (2-4)
    Extremely high (unrealistic) (0-2)

    Then, specify the weight (importance) for Data Requirements as criterion for the assessment
  - **Easy to implement as S/W** - *Assess how easy it will be to implement the model as a S/W tool or component within the SILVANUS Platform.*
    Easy and straightforward (8-10)
    Achievable but with some difficulties (6-8)

  Hard but could be achieved with sufficient resources (4-6)
  Very hard (2-4)
  Extremely hard (unrealistic) (0-2)

  Then, specify the weight (importance) for "Easy to implement as S/W" as criterion for the assessment

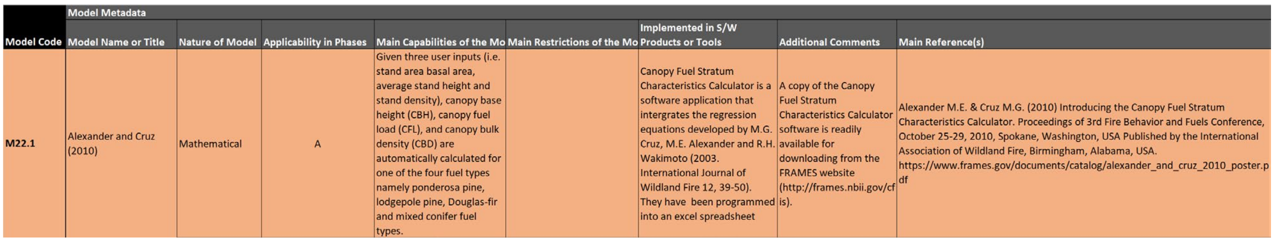
- **Model-specific Criterion A (optional)** - *Specify another relevant criterion (if necessary) for this type of models, or leave blank*

  Then, specify the weight (importance) for "Model-specific Criterion A" as criterion for the assessment

- **Model-specific Criterion B (optional) -** *Specify another relevant criterion (if necessary) for this type of models, or leave blank*

  Then, specify the weight (importance) for "Model-specific Criterion B" as criterion for the assessment

For illustrative purposes, an arbitrary example (row) of “Model Metadata” is provided in Figure 1.



Model Code	Model Metadata							
	Model Name or Title	Nature of Model	Applicability in Phases	Main Capabilities of the Mo	Main Restrictions of the Mo	Implemented in S/W Products or Tools	Additional Comments	Main Reference(s)
M22.1	Alexander and Cruz (2010)	Mathematical	A	Given three user inputs (i.e. stand area basal area, average stand height and stand density), canopy base height (CBH), canopy fuel load (CFL), and canopy bulk density (CBD) are automatically calculated for one of the four fuel types namely ponderosa pine, lodgepole pine, Douglas-fir and mixed conifer fuel types.		Canopy Fuel Stratum Characteristics Calculator is a software application that intergrates the regression equations developed by M.G. Cruz, M.E. Alexander and R.H. Wakimoto (2003. International Journal of Wildland Fire 12, 39-50). They have been programmed into an excel spreadsheet	A copy of the Canopy Fuel Stratum Characteristics Calculator software is readily available for downloading from the FRAMES website (http://frames.nbii.gov/cfis).	Alexander M.E. & Cruz M.G. (2010) Introducing the Canopy Fuel Stratum Characteristics Calculator. Proceedings of 3rd Fire Behavior and Fuels Conference, October 25-29, 2010, Spokane, Washington, USA Published by the International Association of Wildland Fire, Birmingham, Alabama, USA. https://www.frames.gov/documents/catalog/alexander_and_cruz_2010_poster.pdf

Figure 1: Arbitrary example of Model Metadata attributes for a model on canopy fuel load estimation.

Similarly, for the harmonized description of the tools, the attributes (columns) of two tables, i.e. “Tool Metadata” and “Tool Assessment”, had to be filled in. These attributes and their meaning are presented below (note that the categories of models and tools are the same):

- Tool Metadata
  - ***Tool Code*** *– Assign a unique reference code for the identification of the tool, in the form of TXY.Z, where XY is the unique code representing the model’s and tool’s category and Z is a unique number or string uniquely identifying the tool within this category*
  - **Tool Name or Title** - *Specify the name or title of the tool, as most commonly used in the existing literature*
  - **Installability** - *Specify the type of S/W and the H/W or S/W requirements for its successful installation*
  - **Applicability in Phases** - *Specify: A, B, C, or combinations. As a reminder: the three fire management phases are defined as follows (CORDIS 2023): A) Prevention and Preparedness; B) Detection and Response; and C) Restoration and Adaptation*
  - **Main Capabilities of the Tool** - *Specify keywords (free selection) with main capabilities or features of the tool*
  - **Main Restrictions of the Tool** - *Comments on main limitations of the tool*
  - **List of Integrated Models** - *Specify the model(s) that the tool implements and integrates*
  - **Additional Comments** - *Include any additional comments, if necessary*
  - **Main Reference(s)** - *Specify the main references (literature or other sources) that describe or review this tool - Store these resources into the Knowledge Base, if possible in a dedicated folder, e.g. TXY.Z folder*
- Tool Assessment
  - **Functional Suitability and Completeness** - *Degree to which the S/W product or tool provides functions that meet user needs (when used under specified conditions), as well as degree to which the set of functions covers all user objectives in specific operational scenarios. Include a single integer score from 0 to 10. Convention:*

    Excellent (8-10)

    Satisfactory (6-8)

    Moderate (4-6)

    Inadequate (2-4)

    Unacceptable (0-2)

    Then, specify the weight (importance) for Functional Suitability and Completeness as criterion for the assessment

- **Functional Correctness** - *To what extent the outcomes of the S/W product or tool can be considered as correct and precise? Estimate an average value from the evidence that exists in literature resources. Convention:*

  Excellent (8-10)
  Satisfactory (6-8)
  Moderate (4-6)
  Inadequate (2-4)
  Unacceptable (0-2)

  Then, specify the weight (importance) for Functional Correctness as criterion for the assessment
- **Compatibility and Interoperability** - *Degree to which the S/W product or tool can exchange information with other products, systems, or components, and/or perform its required functions while sharing the same H/W or S/W environment. Degree to which a tool can perform its required functions efficiently, exchange information and use the information while sharing a common environment and resources with other products, without detrimental impact on any other product. Specify a single integer score from 0 to 10. Convention:*

  Excellent (8-10)
  Satisfactory (6-8)
  Moderate (4-6)
  Inadequate (2-4)
  Unacceptable (0-2)

  Then, specify the weight (importance) for Compatibility and Interoperability as criterion for the assessment
- **License Type and IPR** - *Assess how open or restrictive the IPR or license type of the tool are. Convention:*

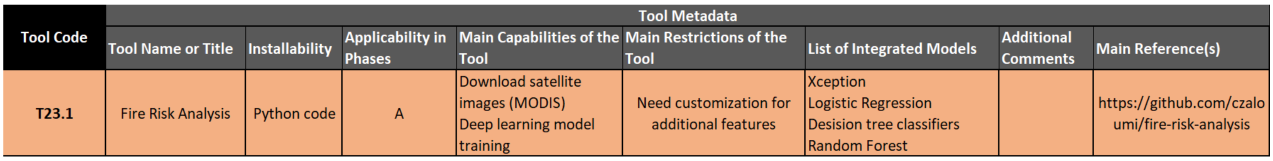
  Open (any restrictions are insignificant) (8-10)
  Few restrictions (6-8)
  Important restrictions (4-6)
  Very important restrictions (2-4)
  Closed or proprietary, with several and severe limitations (0-2)

  Then, specify the weight (importance) for "License Type and IPR" as criterion for the assessment
- **Tool-specific Criterion A (optional)** - *Specify another relevant criterion (if necessary) for this type of models or leave blank.*

  Then, specify the weight (importance) for "Tool-specific Criterion A" as criterion for the assessment
- **Tool-specific Criterion B (optional)** - *Specify another relevant criterion (if necessary) for this type of models or leave blank.*

  Then, specify the weight (importance) for "Tool-specific Criterion B" as criterion for the assessment

From the above, it becomes apparent that a tool might implement or integrate one or several models, whereas a model can be implemented in none, one or several tools (many-to-many relationship). For illustrative purposes, an arbitrary example (row) of "Tool Metadata" is provided in Figure 2.



Tool Code	Tool Metadata							
	Tool Name or Title	Installability	Applicability in Phases	Main Capabilities of the Tool	Main Restrictions of the Tool	List of Integrated Models	Additional Comments	Main Reference(s)
T23.1	Fire Risk Analysis	Python code	A	Download satellite images (MODIS) Deep learning model training	Need customization for additional features	Xception Logistic Regression Desision tree classifiers Random Forest		https://github.com/czalo umi/fire-risk-analysis

Figure 2: Arbitrary example of Tool Metadata completed for a tool on fire risk assessment.

To facilitate the research work, for each model and tool category a specific project partner was assigned as lead contributor, responsible for collecting and analyzing literature sources, research studies and information for that particularly category. Typically, a second project partner was also assigned in the same model and tool category to either support in specific aspects or serve as a peer reviewer. After collecting and analyzing all the relevant information for their model and tool category, the leader was responsible for preparing a report that would be integrated as a dedicated chapter within the present deliverable D2.4.

The general structure of these reports was specified as follows:

- Introduction (about the specific category of forest models and tools)
- Relevant models
    - Overview of relevant models (providing a concise overview in tabular or other applicable format)
    - Description of relevant models (providing concise descriptions and explanations of the relevant forest models citing the corresponding literature sources)
    - Assessment of relevant models (providing a summary assessment of the surveyed models, where applicable, using the criteria specified and explained above)
- Relevant tools
    - Overview of relevant tools (providing a concise overview in tabular or other applicable format)
    - Description of relevant tools (providing concise descriptions and explanations of the relevant forest models citing the corresponding literature sources)
    - Assessment of relevant tools (providing a summary assessment of the surveyed models, where applicable, using the criteria specified and explained above)

It is worth clarifying at this point that the above scheme was meant to provide a basis for information collection, analysis and harmonization. However, as the work of WP2 in SILVANUS is quite broad and extensive, the participating researchers and authors acknowledge that there is no one-size-fits-all solution. Hence, it is possible, when it makes sense, for a report (chapter) to structure its content in a slightly different way, to better adapt to the particularities of the corresponding model and tool category, and thus achieve a clearer and more effective presentation.

Also, it is worth highlighting that the methodology followed for conducting the model and tool assessments (including the relevant limitations) is outlined in appendix 5.1, whereas the results of the assessments are provided in appendices 5.2-5.13, and appropriately cross-referenced from within chapter 2.

The construction of this comprehensive inventory of forest models and tools inside the SILVANUS Knowledge Hub provides several benefits and a significant added value:

A) Point of reference: First, as a standalone outcome, the SILVANUS Knowledge Hub serves as a central point of reference and one-stop-shop that consolidates the state-of-the-art for various categories of forest models and types of tools. To make this Knowledge Hub even more usable for researchers and other stakeholders, SILVANUS evaluates the possibility of gradually evolving it into a web-based tool (i.e., apart from the document format).

B) Fallback and backup: In a modern operational and management platform, such as the one developed and piloted by SILVANUS, several of the employed components and tools in integrated forest management are data-driven. However, in some cases, data are hard to ensure, while in others data-driven solutions might not yet be mature enough to provide reliable solutions. In such cases, having an inventory of forest models and tools that are perhaps simpler, but have been validated in the literature or through past case studies, provides a viable alternative until data-driven solutions become sufficiently mature. Moreover, in some pilots, data sources might be sufficient, while in others data can be hard to get (e.g., due to lack of infrastructure or bureaucratic hurdles). In a modular and configurable platform like SILVANUS, it is possible to configure different pilot deployments in different ways, so as to take advantage of data-driven solutions in pilot sites where this makes sense, while resorting to less data-intensive models and tools in other cases.

C) Baseline for implementation: The models included in this inventory often serve as the basis for being translated into software modules and tools inside the SILVANUS platform. For instance, this is particularly true for models related to climate change impact on forests, models for estimating air quality, etc.

D) Benchmarking and comparison: Modules and tools developed by SILVANUS in other WPs are validated both in the lab as well as in field conditions. The inventory of this Knowledge Hub provides the opportunity and serves as a reference point to find models and tools that can be compared and cross-examined with the novel SILVANUS solutions, in order to identify and better assess strengths and weaknesses.

E) Combination and integration: In a modular and configurable platform like SILVANUS, it is often the case that a user needs to have access to multiple results, coming from various possible methods, instead of a single one. This is because the user needs to either compare or combine results from different methods, for instance if the problem addressed is very complex or critical, or if it is uncertain whether the conditions for using the default method or model are met. Hence, this Knowledge Hub provides the opportunity to SILVANUS developers to provide users with more options and results, where applicable.

The chapters that follow (2.2-2.21) elaborate on the forest models and tools that belong to the specified categories of the Knowledge Hub.

2.2 M11: Strategies and methodologies for resource deployment and management tactics

2.2.1 Introduction

Wildfires are recurrent natural events that have been increasing in frequency and severity in recent decades. They threaten human lives and damage ecosystems and infrastructure, leading to high recovery costs. To address the issue of wildfires, several activities must be managed and coordinated in order to develop a suitable response that is both effective and affordable. This includes actions taken before (mitigation, prevention, and preparedness), during (response), and after the event (recovery). Considering the available resources and the safety of the involved personnel is a key aspect. This chapter is a review focused on fire suppression, which comprises actions belonging to the preparedness phase (deployment) and the response phase (dispatching) of the wildfire management scheme. It goes through the models and methodologies that, applying operations research and optimization techniques, address the management of resources to address fire suppression.

Recent studies have shown that wildfires have been increasing in frequency and severity in recent decades. Some reasons for this are related to human activity, for example, arson attacks (Úbeda and Sarricolea 2016) or misuse of fire in certain areas and seasons prone to fire. According to Nagy et al. (Nagy et al. 2018), humans ignited four times as many large fires as lightning, being the dominant source of large fires in the eastern and western U.S. Moreover, an aggressive wildfire suppression policy may lead to a fuel accumulation, which contributes to more intense wildfires (Curt and Fréjaville 2017).

In addition to the direct interaction of humans with forests, global warming is also causing an increase in wildfires. A rapid rise in temperature is expected to lead to a further escalation in the number of wildfires in the near future (Shi et al. 2021). This may be even more alarming due to the fact that forests are more likely to ignite during their period of regeneration (Zylstra 2018), which is increasing since wildfires occur more often.

As wildfires become more frequent and devastating, more personnel and resources are put at disposal to act on them, so the fire suppression costs have risen (Ingalsbee and Raja 2015). Furthermore, the wildland–urban interface (WUI) is rapidly enlarging, since house density is growing and thus the number of threatened houses, so fire suppression costs are expected to continue escalating (Bayham and Yoder 2020). However, adding more resources to the system may not be the ultimate solution. Acquiring more resources would entail their under-utilization during the majority of the season, or their use under situations in which they are not completely adequate (Belval et al. 2020). In this regard, resource scarcity due to limited budgets can be addressed by improving the efficiency of the existing resources (Belval et al. 2020) and taking advantage of weather, fuel, and topographic changes that create containment opportunities to enhance the effectiveness of fire suppression activities (Fernandes et al. 2016). However, this is not easy to implement. Managers usually work under stressful conditions and time-pressure environments, pushing them sometimes to over-allocate resources relative to values protected, creating inefficiencies (Katuwal et al. 2017).

Given the severe consequences of wildfires on ecosystems and human communities, as well as the difficulty and urgency to find solutions, it is not surprising that wildfire managers are always looking for more robust solutions to help them make decisions in such uncertain situations. There are many open problems related to fire management, each requiring a specific solution that may be well determined using operations research (OR) (Rönnqvist et al. 2015). However, most of these problems are interrelated and thus need an integrated framework in order to address several aspects simultaneously.

The role of fire suppression is to control-and ultimately extinguish- destructive wildfires found by the detection systems (Martell 1982). Decisions on how to extinguish a fire are heavily influenced by how the fire grows and develops, depending on weather conditions, terrain features or fuel type, conditions, and attributes. However, they are also influenced by the available resources, and where those are located. Thus, fire suppression management encompasses decisions not only related to directly acting on the fire once it has ignited, but also to arrange all the available resources prior to the beginning of the wildfire.

Martell (1982) divides the fire suppression process into four stages: resource acquisition and strategic deployment, resource mobilization, initial attack (IA) dispatching, and extended attack (EA) management.

The first phase includes all the long-term decisions to make before the fire, which will heavily influence the others. The second, related to resource mobilization, deals with how the acquired resources are distributed between the bases, where the resources will await to be dispatched in an initial attack. This distribution can be performed at the beginning of the fire season, but it may change depending on fire occurrences (Chow and Regan 2011).

Initial attack (IA) is an aggressive way of extinguishing the fire with the first resources to arrive. It is focused on arranging the deployed resources, deciding on the strategies to be used and how to implement them to prevent the fire escaping control. If the initial attack fails, an extended attack is needed. Extended attack (EA) comprises two key stages: containment and control. Containment entails the creation of control lines that are expected to hold the fire spread. Control deals with the completion of a control line around the fire, any spot fires, and any other interior areas to be saved as well as the cooling down of any hotspot that may be a threat to the constructed control line.

This fire suppression scheme comprehends decisions corresponding to the preparedness stage of a disaster (long-term decisions in acquisition and deployment of resources to bases) and others corresponding to the response stage (resource mobilization, initial attack, and extended attack). The inherent interrelation between these stages makes it almost impossible to develop a specific plan for one of them exclusively. In this regard, operations research can provide integrated tools that help decision-makers determine alternatives.

To develop a suitable fire suppression strategy, a significant amount of information is needed. To anticipate and manage the extinguishment of the fire as fast and efficiently as possible, its behaviour must be predicted, due to its uncertain nature. In this regard, fire growth simulation models are a good forecasting tool. More static information, but useful for long-term planning, is provided by risk maps and indices that help identify the best strategy (Rideout et al. 2017; Rodríguez y Silva et al. 2020). All these indices and simulations need empirical and reliable data to work with, so geographic information systems (GISs) and historical data are often used when available.

To support the wildfire suppression activities and to support development of effective models and tools for this purpose, an overview is provided of existing models and tools used for resource deployment and management tactics in prevention and preparedness, response and recovery phase of a wildfire. The literature sources include the scientific publications registered in the following databases: Scopus, Science Direct, Web of Science, Springer Link, and Science Open databases. Multiple keywords were used to find the most relevant literature sources. The documents were identified with advanced search query strings such as “(Decision making OR Optimisation OR Optimization) AND (Dispatching OR Fire suppression) AND

(GIS OR Geospatial analyses OR Mapping) AND (Wildfire OR Forest fire OR Wildland fire) AND (Mathematical model OR Modeling OR Simulation)". The different keywords used were based on the various subjects that characterize the main research object.

2.2.2 *Relevant models*

2.2.2.1 *Overview of relevant models*

Table 1 summarizes existing models that are relevant to strategies or methodologies for resource deployment as well as to management tactics to mitigate forest wildfires. The most relevant models to WUI areas are also noted in the last column (Capabilities / Restrictions of the Model), whereas a model's applicability across the three fire management phases (i.e., A - prevention and preparedness, B - detection and response, or C - restoration and adaptation) is indicated as well.

Table 1: Overview of models related to strategies or methodologies for resource deployment and management to mitigate forest wildfires.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M11.1	Butler and Cohen (1998)	Mathematical	B	Estimation of safety zones for firefighters	3-surface theoretical model that describes the net radiant energy transfer to a firefighter standing a specified distance from a fire of specified height.
M11.2	Zarate et al. (2008)	Mathematical	B	Estimation of safety zones for firefighters	Estimate the thermal radiation emitted by the flame front of a wildland fire.
M11.3	Knight and Sullivan (2004)	Mathematical	B	Estimation of safety zones for firefighters	Online tool for mapping SSD based on vegetation height, terrain slope, wind speed, and burning condition: the Safe Separation Distance Evaluator (SSDE). Allows users to draw a potential SZ polygon and estimate SSD and the extent to which that SZ polygon may be suitable, given the local landscape, weather, and fire conditions
M11.4	Rossi et al. (2011)	Mathematical	B	Estimation of safety zones for firefighters	Improved solid-flame model approximation to obtain a simple and useful formulation of this Acceptable Safety Distance (ASD).
M11.5	Campbell et al. (2017)	Mathematical	B	Estimation of safety zones for firefighters	Algorithm for calculating pixel-based and polygon-based Safe Separation

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
					Distances (SSDS) from lidar data.
M11.6	Campbell et al. (2022)	Mathematical	B	Estimation of safety zones for firefighters	Safe Separation Distance Evaluator (SSDE) algorithm which is built and applied in Google Earth Engine (GEE), a cloud-based platform for processing and analyzing GIS and remotely sensed data, using the JavaScript application programing interface.
M11.7	NFPA 1051 Standard	Standard	B	Standard for Wildland Firefighting Personnel Professional Qualifications	This standard identifies the minimum job performance requirements (JPRs) for wildland fire fighting personnel.
M11.8	NFPA 1140 Standard	Standard	B	Requirements, standards, wildland fire management, professional qualifications.	This standard provides the minimum requirements for wildland fire management and the associated professional qualifications for wildland fire positions.
M11.9	NWGC Incident Report Pocket Guide (IRPG)	Standard/Guide	A, B	Incident, firefighter, guide.	Standards for wildland fire incident response. Provides critical information on operational engagement, risk management, fire environment, all hazard response, and aviation management. Relevant to WUI dynamics.
M11.10	McCarthy et al. (2003)	Empirical	A, B	Wildfires, suppression, resources estimation.	Models derived from collected data on firefighting resource allocation and fire line construction rates, based on multiple linear regression and non-linear regression analysis of the data, have been used to develop a firefighting resources guide for park and forest fire managers.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
					Relevant to WUI dynamics.
M11.11	Majlingova (2012)	Empirical, GIS based.	A, B	Fire trucks deployment, opening up of the territory, GIS	Methodology to identify the zone where the terrain is accessible for mobile fire appliance apparatus and the losses in fire hose piping are admissible. It was based on computation of the maximum range of fire hose piping (maximum sidelong distance), roads spacing and the index of forest opening-up. Relevant to WUI dynamics.
M11.12	Kapusniak, Majlingova (2015)	Empirical, GIS based, MCA	A, B	Fire trucks deployment, optimization.	Optimization of selecting the fire truck type based on terrain parameters and soil capacity of any locality, forest stand as well as operational and tactical parameters of available fire trucks.
M11.13	Standards of the Fire and Rescue System in Slovakia	Standard/Guide, Mathematical	A, B	Wildfire area, forces and resources estimation, the amount of water required for extinguishing.	Standards to estimate the area of a wildfire and further number of forces and resources estimation to be deployed to suppress the fire and also estimation of an amount of water required for extinguishing. Relevant to WUI dynamics.
M11.14	Suarez et al. (2016)	Mathematical	A	Allocating and deploying resources, locating temporary operations centers (TOCs)	Uses a methodology based on a time-expanded graph, which is the main contribution of the work, that allows for modeling the dynamics of the wildfire, or the costs of the routes in a dynamic fashion.
M11.15	Ríos-Mercado (2020)	Mathematical	A	Allocating and deploying resources, optimization	Integrates the calculation of different fire behavior indices with an MILP model that determines the optimal deployment

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
					of brigades. Relevant to WUI dynamics.
M11.16	Dimopoulou and Giannikos (2001)	Mathematical	A	Allocating and deploying resources, optimization	Determines the location of several limited resources to maximize the weighted coverage of the demand points
M11.17	Sakellariou et al. (2020)	Mathematical	A	Allocating and deploying resources, optimization	Selects the optimal location of the fire agency stations and prepositions vehicles, each of which can cover a circle of 31 min radius (maximum time response) considering available road network and realistic travel times, based on the speed limits of the roads and the average velocity of the trucks
M11.18	Zeferino (2020)	Mathematical	A, B	Allocating and deploying resources, optimization	Addresses the allocation of aerial resources for initial and extended attack, maximizing the expected value of the hazard coverage
M11.19	Chow and Regan (2011)	Mathematical	A, B	Allocating and deploying resources, optimization	Allocates aerial resources to a water source, based on a predetermined demand, minimizing deployment time. Takes into account stochasticity on the day-to-day demand due to weather, and considers relocation if beneficial.
M11.20	Wei et al. (2016)	Mathematical	A	Allocating and deploying resources, optimization	A simulation–optimization procedure to share crews and engines between dispatch zones.
M11.21	Hartnell (1995)	Mathematical	B	Dispatching resources	Complete deterministic discrete-time model for the spread and containment of fire.
M11.22	Donovan, Rideout (2003)	Mathematical	B	Dispatching resources, optimization,	MILP model in which the needed resources are

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
				C+NVC function, fire line based model	optimized to achieve the minimum value of C+NVC.
M11.23	Hu and Ntaimo (2009)	Mathematical	B	Dispatching resources, optimization, C+NVC function, fire line based model	MILP model determines a series of resources that will be dispatched to contain the fire (by having a fire line construction rate faster than the perimeter growth).
M11.24	Rodríguez-Veiga et al. (2018)	Mathematical	B	Dispatching resources, optimization, C+NVC function, fire line based model	MILP model selects the resources needed for forest fire suppression. The formulation addresses maximum flight times and the required rest breaks for air resources and maximum daily operation time for brigades.
M11.25	Yang et al. (2019)	Mathematical	B	Dispatching resources, optimization, fire point based model, Wangzhengfei fire simulation scheme	Two-layer emergency logistic system with a single depot and multiple demand sites. Vehicle routing problem (VRP) is solved where the vehicles, starting from their depots, may serve several sites along their routes.
M11.26	Wu et al. (2019)	Mathematical	B	Dispatching resources, optimization, fire point based model, Wangzhengfei fire simulation scheme	Provides optimal schedule for dispatching the firefighting teams suitably to extinguish several prioritized fire points depending on the severity of the fire in each of them, including constraints that force the first M points with higher priority levels to be visited first
M11.27	Wang et al. (2020)	Mathematical	B	Dispatching resources, optimization, fire point based model, Pareto solution,	Multiobjective model, minimizing travel distance as well as also total rescue time as the main objective.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
				fuzzy logic, ϵ-constraint method.	
M11.28	Bodaghi et al. (2020)	Mathematical	B	Dispatching resources, optimization, fire point based model, Monte Carlo simulation.	Determines the sequence of demand points to be visited by the chosen vehicles, minimizing the weighted sum of the completion times of the operations.
M11.29	Shahidi et al. (2022)	Mathematical	B	Dispatching resources, optimization, fire point based model, greedy algorithm.	Novel approach in which aerial and ground resources are coordinated, in order to cover the demand of several points. This demand is modeled as the necessary time spent by ground resources or the amount of water in liters discharged by the aerial resources. Relevant to WUI dynamics.
M11.30	Shahparvari et al. (2021)	Mathematical	B	Dispatching resources, optimization, fire point based model, greedy algorithm.	Determines the scheduling of several tasks that should be completed in order to contain the fire. Each of them is assigned with a certain number of resources as a demand to be covered.
M11.31	Alvelos (2018)	Mathematical	B	Dispatching resources, optimization, grid-based models, objective function.	Determines fire arrival times for any objective function, instead of using an iterative scheme.
M11.32	Mendes and Alvelos (2022)	Mathematical	B	Dispatching resources, optimization, grid-based models, heuristic iterated local search.	Improvement of the solving times compared with the exact model (CPLEX).
M11.33	Belval et al. (2015)	Mathematical	B	Dispatching resources, optimization, grid-based models, FlamMap.	Determines the fire arrival time to each cell.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M11.34	Belval et al. (2016)	Mathematical	B	Dispatching resources, optimization, grid-based models,	Introducing stochastic weather trees, resources could be dispatched attending to non-anticipativity constraints, which allow for a better interaction between fire spread and fire suppression.
M11.35	Belval and Wei (2019)	Mathematical	B	Dispatching resources, optimization, grid-based models.	Model imposes continuity on the suppression operations and the placing of controls.
M11.36	Homchaudhuri et al. (2013)	Mathematical	B	Dispatching resources, optimization, grid-based models, fire spread.	A simulation–optimization scheme of fire spread.
M11.37	Wei et al. (2018)	Mathematical	B	Dispatching resources, optimization, POD based models.	MILP model to aggregate POD structures into a response POD (rPOD) for containing large fires—a patch between PODs is created using adjacency relationships, where containment lines are established along the boundaries of the rPOD.
M11.38	Wei et al. (2019)	Mathematical	B	Dispatching resources, optimization, POD based models.	Improves the development of rPODs considering fire spread probabilities and spread rates. This allows for determining the order in which the PODs are adhered to the rPOD within a set of periods, estimating fire arrival time to the boundary as the earliest.
M11.39	Wei et al. (2021)	Mathematical	B	Dispatching resources, optimization, POD based models.	Extended models from Wei et al. (2018, 2019) to evaluate the effectiveness of contingency strategies under randomly generated scenarios through an MILP model.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M11.40	Chan et al. (2020)	Mathematical	B	Dispatching resources, optimization.	Developed a strategy in three phases called "Firefly". First, a set coverage problem is identified, which maximizes the area explored by a number of deployed drones. second phase estimates the utility of the cells not assessed. Third, a knapsack problem is solved to maximize the utility of the chosen areas where the brigades are going to be dispatched to, modeling the space as a graph.
M11.41	Rodríguez-Veiga et al. (2018)	Mathematical	B	Dispatching resources, optimization, allocation of aerial resources.	Two linear integer programming models to solve two different decision problems related to the allocation of aerial resources, wherein flying routes should be optimized and monitored to avoid and reduce the risk of collision.
M11.42	Haight and Fried (2007)	Mathematical, MILP model	A, B	Preparedness and response, combined approaches, stochastic model, optimization.	MILP model for the deployment of resources called standard response model (SRM). Scenarios are created using CFES2, which represent the daily number, location, and intensity of the fires. For each fire the standard response required is calculated as the "desired number of resources that can reach the fire within a specified response time".
M11.43	Yohan et al. (2014)	Mathematical, MILP model	A, B	Preparedness and response, combined approaches, optimization.	Two-stage model for deployment and dispatch that minimizes the expected number of fires not receiving a predefined response. This response is also defined as the required number of

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
					resources that can reach the fire within a maximum time.
M11.44	Ntaimo et al. (2012)	Mathematical, MILP model	A, B	Preparedness and response, combined approaches, optimization.	Model considering that resources can be moved between their bases before a fire occurs.
M11.45	Gallego Arrubla et al. (2014)	Mathematical	A, B	Preparedness and response, combined approaches, optimization.	One-stage MILP model includes stochasticity for resource pre-allocation, deployment, and dispatch of dozers. Combining a fire behavior simulator and a wildfire risk model with a probabilistically constrained stochastic MILP, they account for the risk-aversion of the fire manager, integrating expert knowledge.
M11.46	Sakellariou et al. (2020)	Mathematical	A, B	Preparedness and response, combined approaches, optimization.	Provides methodology with two modules, aimed at covering the maximum population served within the predefined time frame.
M11.47	Zhou and Erdogan (2019)	Mathematical	A, B	Preparedness and response, combined approaches, optimization.	Minimizing the people at risk who need to be evacuated, minimizing also the total expected cost of hiring additional on-duty resources. Relevant to WUI dynamics.
M11.48	Wei et al. (2015)	Mathematical	A, B	Preparedness and response, combined approaches, optimization.	includes endogenously designed dispatch rules into resources acquisition Includes endogenously designed dispatch rules into resources acquisition and deployment decisions. However, it still assumes that the manager could anticipate the fire locations and their features before creating

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
					the dispatch plan for each day.

2.2.2.2 Description of relevant models

Evaluating safe separation distance for effective safety zones

Safety zones (SZs) are critical tools that can be used by wildland firefighters to avoid injury or fatality when engaging a fire. Effective SZs provide safe separation distance (SSD) from surrounding flames, ensuring that a fire's heat cannot cause burn injury to firefighters within the SZ. Evaluating SSD on the ground can be challenging, and underestimating SSD can be fatal. Several methods / models are presented, which are used to determine the safe separation distance (SSD) from the flames.

Butler and Cohen (1998) presented a 3-surface theoretical model that describes the net radiant energy transfer to a firefighter standing a specified distance from a fire of specified height. Model predictions compare favorably with qualitative data from entrapments on four wildfires and two previously published models. The flame was approximated as a flat sheet of given height and width with uniform temperature and emissivity. The firefighter was approximated as another flat surface. Gray diffuse radiant exchange was assumed. Recommendations: maximum energy exposure limit should be of 7kW/m^2, flame width of 20m, flame emissivity equal to 1, flame temperature 1200K, minimum SSD of four times the flame height as a rule-of thumb for wildland firefighters. Calculations indicate that for most fires, safety zones must be greater than 20 m wide to ensure firefighter survival. A general rule-of-thumb derived from this work is that a safety zone radius must be equal to or greater than 4 times that maximum flame height. Model is better for flames that exceed 10 m. Their work is the basis of official wildland firefighter safety zone guidelines in the United States.

Zarate et al. (2008), for establishing safety zones for people who are intervening in the emergency or attempting evacuation, the solid flame model, together with the view factor calculated from a previously selected equation, used to estimate the thermal radiation emitted by the flame front of a wildland fire. In research, they assumed a flame temperature of 1200 K, flame emissivity of 1, atmospheric transmissivity of 1 and flame width of 20 m. Suggest a mean SSD of 4.8 flame heights for an exposure limit of 4.7kW/m^2 and 3.8 times the flame height for an exposure limit of 7 kW/m^2. They recommend a 20% increase in SSD to account for convection. After determining the flame heights yielded by the 13 fuel types in the Rothermel classification for surface fires, and for crown fires in various Mediterranean forests, the thermal radiation was calculated for each scenario as a function of the distance. These data, together with threshold values for the vulnerability of people (protected or unprotected) and houses to thermal radiation, allowed for a set of safety distances for different situations to be obtained. These safety distances can be applied both in territory planning and in emergency situations.

Knight and Sullivan (2004) introduced a new online tool for mapping SSD based on vegetation height, terrain slope, wind speed, and burning condition: the Safe Separation Distance Evaluator (SSDE). It allows users to draw a potential SZ polygon and estimate SSD and the extent to which that SZ polygon may be suitable, given the local landscape, weather, and fire conditions.

The Safe Separation Distance Evaluator (SSDE) algorithm was built and applied in Google Earth Engine (GEE), a cloud-based platform for processing and analyzing GIS and remotely sensed data, using the JavaScript application programing interface. GEE was selected for few reasons: (1) it enables the production of user-facing applications that can be widely accessed by anyone with an internet connection; (2) it hosts an immense catalog of geospatial data, including datasets necessary for the analysis of SZ suitability; (3) its cloud computing capabilities provide for rapid execution of complex geospatial functions, allowing users to quickly assess SZ suitability. Accordingly, all data processing described in this section is conducted using the GEE.

The SSDE evaluates SSD in two primary ways. The first is per-pixel SSD, which is a representation of how far one must be from that pixel (e.g., in meters) in order to avoid burn injury. This is calculated at the individual pixel level across an entire area of interest based on the vegetation height and terrain slope within each pixel, and user-defined wind speed and burn condition classes. It provides a landscape-scale view of SSD and can be used to aid in the delineation of potential SZ polygons. However, it is perhaps more important to evaluate SSD at the level of the SZ polygon, as this can help fire personnel determine the suitability of a potential SZ. Accordingly, the second way that SSDE evaluates SSD is through the analysis of proportional SSD (pSSD) within potential SZ polygons. pSSD quantifies the extent to which a potential SZ polygon provides SSD from surrounding vegetation/flames, considering the average per-pixel SSD contained within a series of segments (or clusters of contiguous pixels) around the SZ polygon. Measured in percent, a pSSD of 100% or greater for a given pixel would mean that, factoring in vegetation height surrounding the polygon, slope, wind speed, and burn condition, the pixel's location should provide sufficient SSD, should fire personnel opt to use this location as a SZ. Conversely, a pixel with a pSSD of less than 100% would indicate that firefighters located within that pixel may risk injury from burning vegetation outside the boundary of the polygon.

Given the importance of vegetation height for assessing SSD, they also described an analysis that compares LANDFIRE Existing Vegetation Height and a recent Global Ecosystem Dynamics Investigation (GEDI) and Landsat 8 Operational Land Imager (OLI) satellite image-driven forest height dataset to vegetation heights derived from airborne lidar data in three areas of the Western US. This analysis revealed that both LANDFIRE and GEDI/Landsat tended to underestimate vegetation heights, which translates into an underestimation of SSD. To rectify this underestimation, we performed a bias-correction procedure that adjusted vegetation heights to more closely resemble those of the lidar data. SSDE is a tool that can provide valuable safety information to wildland fire personnel who are charged with the critical responsibility of protecting the public and landscapes from increasingly intense and frequent fires in a changing climate. However, as it is based on data that possess inherent uncertainty, it is essential that all SZ polygons evaluated using SSDE are validated on the ground prior to use.

Rossi et al. (2011) proposed an analytical approximation to obtain a simple and useful formulation of this Acceptable Safety Distance (ASD). A sensitivity analysis was conducted on the different physical and geometrical parameters used to define the flame front. This analysis showed that the flame temperature is the most sensitive parameter. The results of the analytical model were compared with the numerical solution of the flame model and previous approaches based only on flame length. The results showed that the analytical model is a good approximation of the numerical approach and displays realistic estimations of the Acceptable Safety Distance for different fire-front characteristics.

An improved solid-flame model developed by Butler and Cohen (1998) and further by Knight, Sullivan (2004) and Zarate et al. (2008) was presented in this study. The fire front was idealized as a solid flame front emitting thermal radiation from its side. The new formulation led to the establishment of a new criterion for estimating the ASD based on the fire-front width. A simplified analytical expression was derived from the model, which allows the determination of the ASD for people as well as for houses or facilities from a simple-to-use formula. Only one parameter needs to be fitted to the solid-flame model. A sensitivity analysis has indicated that the parameters with a significant effect on the estimation of the ASD are the flame temperature and the flame emissivity. If the end-users select a flame temperature or a flame emissivity that are not representative of the actual fire front, the model could provide a bad estimation of the ASD, which would lead to incorrect and dangerous decisions.

Campbell et al. (2017) introduced an algorithm for calculating pixel-based and polygon-based Safe Separation Distances (SSDS) from lidar data. SSDS was calculated for every potential safety zone within a lidar dataset covering Tahoe National Forest, California, USA. A total of 2367 potential safety zones with an SSDS ≥1 were mapped, representing areas that are suitable for fires burning in low wind and low slope conditions. The highest SSDS calculated within the study area was 9.65, a score that represents suitability in the highest wind-steepest slope conditions. Potential safety zones were clustered in space, with areas in the northern and eastern portions of the National Forest containing an abundance of safety zones while areas to the south and west were completely devoid of them. SSDS can be calculated for potential safety zones in advance of firefighting, and can allow firefighters to carefully compare and select safety zones based on their location, terrain, and wind conditions. This technique showed promise as a standard method for objectively identifying and ranking safety zones on a spatial basis.

Campbell et al. (2022) described the Safe Separation Distance Evaluator (SSDE) algorithm which is built and applied in Google Earth Engine (GEE), a cloud-based platform for processing and analyzing GIS and remotely sensed data, using the JavaScript application programing interface. GEE was selected for few reasons: (1) it enables the production of user-facing applications that can be widely accessed by anyone with an internet connection; (2) it hosts an immense catalog of geospatial data, including datasets necessary for the analysis of SZ suitability; (3) its cloud computing capabilities provide for rapid execution of complex geospatial functions, allowing users to quickly assess SZ suitability.

The SSDE evaluates SSD in two primary ways. The first is per-pixel SSD, which is a representation of how far one must be from that pixel (e.g., in meters) in order to avoid burn injury. This is calculated at the individual pixel level across an entire area of interest based on the vegetation height and terrain slope within each pixel, and user-defined wind speed and burn condition classes. It provides a landscape-scale view of SSD and can be used to aid in the delineation of potential SZ polygons. However, it is perhaps more important to evaluate SSD at the level of the SZ polygon, as this can help fire personnel determine the suitability of a potential SZ. Accordingly, the second way that SSDE evaluates SSD is through the analysis of proportional SSD (pSSD) within potential SZ polygons. pSSD quantifies the extent to which a potential SZ polygon provides SSD from surrounding vegetation/flames, considering the average per-pixel SSD contained within a series of segments (or clusters of contiguous pixels) around the SZ polygon. Measured in percent, a pSSD of 100% or greater for a given pixel would mean that, factoring in vegetation height surrounding the polygon, slope, wind speed, and burn condition, the pixel's location should provide sufficient SSD, should fire personnel opt to use this location as a SZ. Conversely, a pixel with a pSSD of less than 100% would indicate that firefighters located within that pixel may risk injury from burning vegetation outside the boundary of the polygon.

NFPA 1051 Standard identifies the minimum job performance requirements (JPRs) for wildland fire fighting personnel. The intent of the technical committee was to develop clear and concise JPRs that can be used to determine that an individual, when measured to the standard, possesses the skills and knowledge to perform as a wildland fire fighter. The committee further contends that these JPRs are applicable to all agencies that respond to wildland fires.

NFPA 1140 Standard, as part of the Emergency Response and Responder Safety Document Consolidation Plan as approved and amended by the NFPA Standards Council, is a combination of Standards NFPA 1051, NFPA 1141, 1143, and NFPA 1144. This standard provides the minimum requirements for wildland fire management and the associated professional qualifications for wildland fire positions. The purpose of this standard is to specify the minimum requirements for the fire protection and emergency services infrastructure in wildland, rural, and suburban areas, wildland fire management practices and policies, methods of assessing wildland fire ignition hazards, and job performance requirements fr wildland fire positions.

NWGC Incident Report Pocket Guide (IRPG) establishes standards for wildland fire incident response. The guide provides critical information on operational engagement, risk management, fire environment, all hazard response, and aviation management. It is a collection of guidelines, checklists, and best practices that have evolved over time within wildland fire operations. The IRPG does not provide absolute solutions to the unlimited number of situations that will occur. Some fire line decisions may be relatively simple; many are not. These decisions often require individual judgment, creativity, and collaboration — skills developed through extensive training, dedicated practice, and experience, which the guide facilitates.

Includes information on separation distance between the firefighter and the flames. This should be at least four times the maximum continuous flame height. Distance separation for flat terrain and no wind is the radius from the center of the safety zone to the nearest fuels. Calculations are based on radiant heat only and do not account for convective heat from wind and/or terrain influences. Since calculations assume no wind and no slope, safety zones downwind or upslope from the fire, it will require to consider with larger separation distances.

McCarthy et al. (2003) collected information on firefighting resource allocation and fire line construction rates achieved in recent actual fire events, with the aim of producing models based on real, and current operational data. Data on fire line conditions and fire line construction rates were collected from 103 fire events spanning the 1997–98 to 2000–01 fire seasons in Victoria. Models of fire line construction rates for hand trail, small bulldozers and large bulldozers were developed based on this data. Some information was also collected in regard to holding rates of ‘wet lines’ using both ground-based tankers and firebombers. Preliminary data on critical resource combinations for containment of various lengths of fire line was also collected. Hand trail construction rates, based on actual fire line data, appeared to be considerably lower than those obtained in the past from demonstration-type situations (e.g. Project Aquarius). The main factors influencing the variation in these construction rates were found to be elevated fuel and terrain class, with average rates (90–120 m/crew/hour) declining quickly when the six-person crew was faced with substantial elevated fuels and/or steep, broken terrain (down to 30–60 m/crew/hour). The main factors influencing construction rates for smaller bulldozers were found to be terrain, debris and operator experience. Operator experience was slightly less important for larger bulldozers, with terrain, debris and rock being the major influencing factors. Resource combinations were not studied in detail, but some combinations which had been found to be successful for containment over a range of fire line lengths and conditions were suggested as the basis for minimum resourcing. Over- and under-resourcing were also briefly considered and found to be fairly uncommon. The models derived from the data, based on multiple linear regression and non-linear regression analysis of the data, have been used to develop a firefighting resources guide for park and forest fire managers.

Majlingova (2012) introduced a simple GIS based approach to the assessment of forest opening-up level from the aspect of terrain accessibility for available mobile fire appliance apparatus with the use of GIS and GNSS technologies. First, the forest road network was mapped using the GNSS technology, then the information about quality of particular roads was collected. In the ArcGIS environment these data were processed and as a result the geodatabase was created. The opening-up analysis was performed for the selected forest management district and available mobile fire appliance apparatus (truck) - pumping appliance CAS 32 on Tatra 148 chassis and forest special fire truck UNIMOG on Mercedes chassis, using the available spatial tools for distance analyses using the grid format of GIS data. The objective of opening-up analysis was to identify the zone where the terrain is accessible for mobile fire appliance apparatus and the losses in fire hose piping are admissible. It was based on computation of the maximum range of fire hose piping (maximum sidelong distance), roads spacing and the index of forest opening-up. Results of this analysis are valuable as a support for decision making process for foresters from the sphere of forest protection, road planning and construction, fire brigades by planning of fire attacks, risk managers and crisis managers.

Kapusniak, Majlingova (2015) introduced the structure of decision-making model to optimize the process of selection of the firefighting equipment to fight the forest fires in the mountainous conditions of Slovakia. The selection of suitable firefighting equipment was based on the multicriterial assessment of fire-fighting equipment technical – operational parameters and natural conditions in locality where a wildfire occurred. The model was built in a decision support systems environment, specifically the NetWeaver programming environment. It was built as a dependency network composed of data links connected by logical links. In the model, the different types of firefighting equipment used for firefighting are considered in terms of natural and operational-technical parameters. The selected types of firefighting equipment suitable for deployment for forest firefighting in mountain conditions in Slovakia were divided into two basic groups:

forest specials and equipment designed to provide shuttle transport of extinguishing medium (water) to the fireground.

In terms of natural and operational-technical parameters, the selection of suitable equipment for forest fire fighting was based on a simultaneous multi-criteria evaluation of groups of natural factors represented by subgroups of soil factors and factors of accessibility of the territory for deployment of ground mobile firefighting equipment. In terms of soil parameters, we assessed soil bearing capacity, which also depends on soil type, and soil condition (wet, dry, frozen). In terms of accessibility, we assessed three groups of factors, the parameters of the road network, the accessibility of the terrain for the deployment of ground mobile firefighting equipment and the extent of the firefighting zone of the ground mobile firefighting equipment, calculated for each stand of vegetation from the road that is passable for the firefighting equipment. They determined the firefighting zone and its extent for each stand according to the modified methodology presented in Majlingová (2012). Factors such as obstacles (cliffs, rocks, ravines, etc.) and slope accessibility entered into the assessment of terrain accessibility for the deployment of ground mobile firefighting equipment.

The technical and operational conditions were evaluated based on the selected critical parameters of the firefighting equipment (fire trucks). The selection and use of suitable firefighting equipment was, in the case of the evaluation of its technical parameters, directly linked to the parameters of the environment for which we perform the deployment suitability analysis.

The decision network (model) was built from data links representing the individual factors under consideration, interconnected by logical links (AND function - represents simultaneous evaluation of several defined factors → multicriteria decision making). The selection of each type of firefighting equipment on the basis of the assessment of the individual factors entering the decision, from the lower levels (input data to the decision) to the highest, was based on a sequential evaluation in terms of the defined factors, for which they defined a selection rule based on fuzzy logic (uncertainty principle). This means that each type of technique was successively evaluated on the basis of the factors defined in the network (in a bottom-up direction, with the identified optimal variant at the top of the network - the pyramid principle), based on the input values obtained from the underlying data (analysis results, GIS data, technical parameters, etc.). In terms of fuzzy logic rules, these are assessed in terms of predefined intervals of values into suitable (value 1) and unsuitable (value 0). Only those assets that passed the lower level assessment were promoted to the higher level assessment. In the decision-making (analysis) process, all defined types of firefighting equipment were considered simultaneously. At the top (end of the analysis), only those that were optimal and satisfy all criteria at all levels were assigned with resulting value of 1.

However, the result of the evaluation (analysis) was not only the determination of the optimal variant but in the database, which is the output of the decision-making process, all types of equipment under consideration were evaluated and each was assigned a suitability value in the interval 0-1. The closer the resulting value is to 1, the more suitable a given type of firefighting equipment was for deployment in the conditions of a given environment. In addition to the results of the overall assessment (of the whole network of factors), the database also contains results (suitability values in the interval [0; -1]) for individual groups of factors at individual levels as well as for the factors under consideration themselves = comprehensive assessment results.

By linking the NetWeaver environment with the EMDS environment, they obtained a visualization of the assessment results in a GIS environment.

Standards of the Fire and Rescue System in Slovakia lists the determinants and parameters of fire relevant to fire tactics, including the definition of 3 fire zones (burning zone, preparation zone and smoke zone). In addition, it provides mathematical models for calculating the area of the fire, the depth of extinguishment, for calculating the necessary quantity of extinguishing agent to ensure its continuous supply to the fireground, also mathematical models for determining the number of firefighters needed to fight the fire.

Allocating and Deploying Resources

To elaborate the next part of model review, the work of Granda et al. (2023) was used as a primary source of knowledge and information.

In the fire suppression paradigm, there is much work to be done before the actual fire starts. Planning is key for a good development of the fire suppression strategy and some decisions should be taken in advance: acquisition of material, hiring of personnel, and allocation of resources to bases, or even the decisions on where to locate these bases. (Granda et al. 2023)

Suarez et al. (2016) address the problem of locating temporary operations centers (TOCs), which will serve as coordination centers for deploying resources. They use a methodology based on a time-expanded graph, which is the main contribution of the work, that allows for modeling the dynamics of the wildfire, or the costs of the routes in a dynamic fashion. The set of nodes of the graph is divided between candidate nodes for facilities or TOCs and demand points; the arcs account for transportation costs and time, depending on the quality of the roads. The model is a two-stage stochastic mixed integer linear programming model (MILP). In the first stage, it minimizes the costs of opening TOCs and placement of inventory resources in them. In the second, the costs of distribution and some penalties related to excess and shortage of inventory are also minimized. Stochasticity is applied in the form of scenarios with associated probabilities in the second stage.

Ríos-Mercado (2020) integrates the calculation of different fire behavior indices with an MILP model that determines the optimal deployment of brigades. The first step is calculating the potential risk of fires, based on GIS information of the area. Then, the areas are classified according to their risks and importance.

Last, an MILP model developed by **Dimopoulou and Giannikos** (2001) is run to determine the location of several limited resources to maximize the weighted coverage of the demand points.

Another approach on how to allocate resources is based on the response times of the available resources and the area they can cover within that time.

Sakellariou et al. (2020) predicted a burning probability for each fire-prone region and propose an MILP model whose objective is maximizing the covered area. The model selects the optimal location of the fire agency stations and prepositions vehicles, each of which can cover a circle of 31 min radius (maximum time response) considering available road network and realistic travel times, based on the speed limits of the roads and the average velocity of the trucks.

In the same vein, **Zeferino (2020)** addresses the allocation of aerial resources for initial and extended attack, maximizing the expected value of the hazard coverage (Verde and Zêzere 2010). In this case, aircrafts are allocated based on their response time, which gives a radius of action. The main contribution of this work is that it explicitly considers redundancy in the allocation of the aerial resources, considering the unavailability of some aircrafts due to maintenance tasks or rest periods. Nevertheless, no attention is paid to the actual time the resources may take to reach each point, but only to the radius of action of the aircraft.

Normally, at the beginning of the season, the resources are deployed to their homebases so as to be prepared for the fire season, considering their optimal allocation for minimizing their movement when needed, as studied in (Sakellariou et al. (2020); Zeferino (2020)). However, due to the stochasticity of fire occurrence, some benefits may be drawn from a system in which relocation is allowed and optimized, providing a more dynamic framework.

Chow and Regan (2011) present a static standard p-median formulation that allocates aerial resources to a water source, based on a predetermined demand, minimizing deployment time. This model is then extended into the time dimension to obtain a chance-constrained dynamic relocation model. The dynamic extension of the model takes into account stochasticity on the day-to-day demand due to weather, and considers relocation if beneficial. To avoid complexity, the authors propose the evaluation of the relocation using a rolling horizon of seven days. The authors acknowledge that the dynamic formulation may be less cost-effective, but achieves better results regarding suppression effectiveness. A shortcoming of the model is that in the demand forecast, the burning indices for all nodes are assumed to be independent of each other, whereas in fact there is a close relationship between the burning index and actual fire occurrence in adjacent nodes.

Addressing relocation matters as well, **Wei et al. (2016)** present a simulation–optimization procedure to share crews and engines between dispatch zones. They address issues related to shift length, but also the effect of resource drawdown policies, which is not previously addressed in the literature. Resource drawdowns are the number of resources that should be held in their homebases for initial attack assignment and are unavailable for use outside their local areas. A level of demand is determined using regression models, calculating available resources as the maximum dispatched historically. The MILP model minimizes resource movement distances as a proxy of costs. A limitation of the model is that the surplus of resources is not deemed beneficial, which may be useful for building additional fire lines; moreover, they do not allow for substitutions between crews and engines to cover demand, while covering a demand with a different resource than requested may be more beneficial than not sending any resources whatsoever.

Dispatching Resources

Once a fire has started, fire managers need to respond to it, deciding which resources to dispatch, where, and when. The models in this section mainly address how to optimally dispatch the available resources to contain and control the fire.

From a theoretical point of view, the fire-fighter problem has drawn attention from several researchers since proposed in a 1995 conference by **Hartnell (1995)**. It is an NP-complete deterministic discrete-time model for the spread and containment of fire. Although many methods have been applied to solve it (Blum et al. 2014; Hu et al. 2015; Michalak 2014; Ramos et al. 2020), they mostly analyze the mathematical aspects of the problem and do not deal with real cases.

There exist more complex and realistic methodologies, including completion times, or modeling of the fire spread more accurately. Some of them use existing simulators to predict fire behavior, or to combine it with the fire suppression process, to create an integrated strategy. This is important as fire suppression actions severely affect the behavior of the wildfire, changing its final shape and perimeter (Wei et al. 2011). Many strategies for wildfire suppression optimization have been tested using OR methodologies, since different methods and approaches may better characterize some aspects over others. In this section, resource dispatch models have been classified based on these different approaches.

Fire-Line Based Models

In models of this kind, the containment condition of the fire is that the built fire line is greater than the fire perimeter. They are normally fed with information regarding fire spread rate and the rate at which the resources can build a fire line, in order to contain the fire. The objective is to minimize the sum of all costs and damages, using the Cost plus net value (C+NVC) methodology. This methodology accounts for the pre-suppression costs (related to wildfire management prior to a fire season), suppression costs (expenditures related to the direct fire management during fire season), and NVC (net wildfire damages).

Some authors have used the C+NVC methodology in a theoretical framework for wildfire management, but **Donovan and Rideout (2003)** developed an MILP model in which the needed resources are optimized to achieve the minimum value of C+NVC. It is based on a knapsack problem, including a temporal dimension for dispatching several resources to contain a fire—it does not work with multiple fires. The fire perimeter is precomputed using Farsite, and resources have to be dispatched in given time periods to build a fire line faster than the perimeter growth, which is assumed to be completed at the end of the optimization horizon. It assumes that a contained fire will be extinguished—an escaped fire would give rise to infeasibilities in the model. A limitation of this model is that it only determines the mix of resources needed, but does not provide details about the strategy.

Also using the C+NVC function, **Hu and Ntaimo (2009)** developed a stochastic extension of the model in Donovan and Rideout (2003), that does not work with escaped fires either. This comprises an integrated simulation–optimization framework that combines fire simulation, resources optimization, and fire suppression simulation in a feedback loop, which may include expert knowledge calibrations between iterations. First, a set of fires is simulated using DEVS-FIRE to determine the fire perimeter. Then, a two-stage MILP model is developed, using several scenarios. In its first stage, pre-suppression plus expected suppression costs and NVC of the burned area are minimized. In the second stage, the suppression costs and a penalty for the uncovered perimeter for each scenario are minimized. The MILP model determines a series of resources that will be dispatched to contain the fire (by having a fire Dispatching resources, optimization, C+NVC function line construction rate faster than the perimeter growth). This fire-suppression strategy is then tuned with a simulation model, in which different attack techniques are coded. This approach may be interesting because it provides a few different strategies to choose from. Nevertheless, this iterative approach may not be operational due to the short decision times.

Also using the C+NVC methodology, **Rodríguez-Veiga et al. (2018)** developed an MILP model that selects the resources needed for forest fire suppression. The formulation addresses maximum flight times and the required rest breaks for air resources and maximum daily operation time for brigades. A fire simulator estimates the growth of the fire perimeter, with no update; with this information, the model aims to dispatch resources that can build a fire line faster than the perimeter growth. If fire containment is not achieved in the optimization horizon, infeasibilities may arise, so a second and simpler model is built to focus on the maximization of the resource performance, only considering time constraints but not the evolution of the fire. The main contribution of this model is considering several resources with different fire line production rates, combining air and ground resources.

However, as Hu and Ntaimo (2009) acknowledge, these methodologies are simplistic, since they do not account for the interaction between fire spread and suppression, and thus tend to overestimate the resources that are needed.

Fire Points-Based Models

A more general approach is considering that there are several fire events, so the resources must be dispatched to a number of locations to cover a set of demand points. Usually, a group of teams have to visit each of the points to address the demand. The fire is considered to be contained when all the fire points have been visited and provided with the necessary resources, or enough time has been spent on them. This problem is based on the vehicle routing problem (VRP), as some authors acknowledge.

Yang et al. (2019) built a two-layer emergency logistic system with a single depot and multiple demand sites. The Wangzhengfei fire simulation determines the fire propagation, and then each fire site is prioritized based on its emergency level. In the second layer, a vehicle routing problem (VRP) is solved where the vehicles, starting from their depots, may serve several sites along their routes. Two ways of solving the problem are proposed, depending on the fire spread velocity. For fast propagation, the focus is on extinguishing the fire as soon as possible, which is achieved when the rate of increase in the burned area is null, whereas for slow propagation, an immune clonal algorithm is used to minimize travel times and costs, determining the necessary resources in each fire-point based on fire spread velocity. The main contribution of the study is that, between the mentioned models in this section, it is the only one that considers a bound on the time for the resources to arrive to a node. However, it does not consider the completion times of the tasks in each node.

Wu et al. (2019), also using the Wangzhengfei fire simulation scheme, determined fire spread, wherein speed is included in the MIP model to determine completion times at each point in a dynamic fashion. It considers a problem similar to a VRP in which the temporal scope is important. The objective is to find an optimal schedule for dispatching the firefighting teams suitably to extinguish several prioritized fire points depending on the severity of the fire in each of them, including constraints that force the first M points with higher priority levels to be visited first. The problem is considered on an undirected graph, minimizing the total distance traveled by all firefighting teams and assuming that the available resources are sufficient to extinguish the fire.

Wang et al. (2020) take the model from Wu et al. (2019) and transform it into a multiobjective model, minimizing travel distance as well as also total rescue time as the main objective. The main contribution of this paper is the calculation of the Pareto solution, which may be useful for providing different alternatives for the fire manager to choose from. In this approach, fuzzy logic and the ϵ-constraint method are used. However, as the authors acknowledge, the problem is difficult to rapidly solve by commercial software such as CPLEX.

Bodaghi et al. (2020) proposed a methodology that determines the sequence of demand points to be visited by the chosen vehicles, minimizing the weighted sum of the completion times of the operations. The model itself is deterministic in nature, but the methodology includes a loop that varies the input parameters in a stochastic fashion using Monte Carlo simulations to create different scenarios. It can be used in any disaster relief operation requiring the transportation of resources. Specifically, the authors test the methodology using real data from a bushfire in Australia. The main contribution is that it integrates sequencing and scheduling of resources, considering uncertainty. It also benefits from GIS information on fast and safe travel routes. Moreover, the completion times are stochastic, based on stochastic time processing and demands at each point.

Shahidi et al. (2022) modeled a more complex situation, with a novel approach in which aerial and ground resources are coordinated in order to cover the demand of several points. This demand is modeled as the necessary time spent by ground resources or the amount of water in liters discharged by the aerial resources. Moreover, despite the fact that in previous models each node was attended to by only one vehicle or resource, in this case several ground resources can be combined to cover the demand faster. The main contribution of this approach is thus the coordination of aerial and ground resource operations which makes the model more realistic, proposing a novel VRP that accounts for the refill of the aerial resources. The authors solve the test cases with a new proposed greedy algorithm, since they found CPLEX incapable of solving the problem in real-world scales.

Shahparvari et al. (2021) determined the scheduling of several tasks that should be completed in order to contain the fire. Each of them is assigned with a certain number of resources as a demand to be covered. The model is bi-objective, minimizing firstly the total time taken to complete all activities and secondly the shortages in resources. The novelty of this study resides in their proposed time-based decomposition approach (greedy), called Coordination algorithm, that outperforms both a genetic algorithm and the exact solution approach, as well as the consideration of precedence constraints for operations and time windows.

Grid-Based Models

In these approaches, the space is discretized into a grid, in which each cell may have different characteristics, accounting for heterogeneity between them. This is of special importance to easily integrate GIS data, which provide realistic information about the landscape. The remarkable feature of these models is that they allow for the interaction between fire spread and suppression, leading to more realistic strategies, and avoiding the overestimation of resources. In this case, the fire behavior is not modeled by a simulator, but integrated in the very optimization model, in a way that the simulation of fire spread and the optimization of the resources are performed simultaneously, affecting one another. The suppression strategy relies on the placement of controls. Controlled cells are cells on which a treatment has been performed to stop or delay the fire spread.

An example of these models is developed by Wei et al. (2011). Fire behavior parameters are calculated using FlamMap and fed into a base MILP model, that tries to stop the fire spread as early as possible, considering the minimum travel time (MTT) of fire. Previous models using the MTT methodology within an MILP model failed to correctly determine the fire arrival time for those cells not in the binding burning path

(Hof et al. 2000). To overcome this issue, two iterative approaches are developed, running a time correct model. Discretizing the time in short periods makes it possible to limit the number of resources available in each of them. The objective is to minimize the sum of fire loss across all burned cells, assuming that controlling a cell interrupts the fire spread to adjacent cells. It also includes the firefighter's safety concerns regarding fire intensity thresholds. The model is deterministic with respect to weather conditions, fire spread, and availability of suppression resources. The major contribution is that this methodology accounts for the interaction between fire growth and suppression, using the corrected MTT methodology. However, the model is still simplistic because it does not consider completion times, nor the movement of the brigades, and it only limits the number of controls that can be allocated in each period, but permits simultaneity of the controls as long as they do not exceed the number allowed.

Alvelos (2018) transformed an optimization problem into a feasibility problem. This includes all the necessary constraints to correctly determine fire arrival times for any objective function, instead of using an iterative scheme such as the one by Wei et al. (2011). The approach is based on the MTT methodology solving the shortest path problem by the Dijkstra algorithm and taking into consideration how fire suppression actions hinder the progress of fire. The author tested several objectives. This approach does not consider completion nor traveling times between controls either, it only defines time instants where the resources become available, to avoid having unlimited resources. As Alvelos (2018) recognizes, obtaining good quality solutions for large real instances is a major challenge for the future.

Mendes and Alvelos (2022) took the model and solve it using a heuristic iterated local search. One of the major benefits of using this approach is the improvement of the solving times compared with the exact model (CPLEX) used by Alvelos (2018), which increases with the grid size.

Belval et al. (2015) proposed a similar integrated methodology to correctly determine the fire arrival time to each cell. A new feature of this model is that fire intensity is calculated in a spatially dynamic fashion, tracking the binding paths of the fire, instead of taking this information from fire simulators as most of the models do. Based on the intensity, the concept of beneficial fires is introduced, exploring fire management objectives different from just containment. In one of the case studies, the authors examine how fire behavior can be altered rather than just suppressed, using a multiobjective approach. The information on fire spread rates to determine fire arrival times and intensities is deterministic and taken from FlamMap. A major issue remains unaddressed since the resources are assumed to be unlimited, and the timing of the controls is not determined correctly, not addressing the problem of simultaneous controls nor considering completion times before fire arrival.

In order to limit the resources, **Belval et al. (2016)** presented a multistage model based on Belval et al. (2015). Introducing stochastic weather trees, resources have to be dispatched attending to non-anticipativity constraints, which allow for a better interaction between fire spread and fire suppression. Stochasticity affects fire spread rates, whereas including stochastic weather trees is a major contribution of the model, as it entails large running times, or even the inability of solving the problem if beneficial fires are considered (the exact algorithm cannot close the gap). This does not solve the problem of simultaneity of controls either, since it only restricts their number within each period.

Although the mentioned grid-based models include some constraints limiting the resources and their availability times, they do it in a simplistic way. Belval et al. (2015) only limit the controls in cells not reachable in the response time by forbidding the placement of controls in certain precalculated cells, but assume that resources are unlimited. Wei et al. (2011) and Belval et al. (2016) limit the number of controls to be placed in each stage to reflect limited resources, but do not include specific time constraints related to fire arrival time or to avoid simultaneity of controls within each period. Something similar occurs in the models by Alvelos (2018) and Mendes and Alvelos (2022), where resources are made available in certain time instants, avoiding simultaneity, but not considering fire arrival times related to the timing of the controls. Moreover, these models do not impose continuity on the suppression operations and the placing of controls.

Belval and Wei (2019) are the first authors that fully address this problem. Given a grid with an ignition point, the model simulates the movement of the fire using the MTT methodology and determines the cells/nodes in which suppression is needed (controls). A brigade, responsible of placing the controls, travels between adjacent nodes, spending time in traveling and also some extra time if a control in a cell is needed. The fire intensity is modeled in a spatially dynamic fashion as in Belval et al. (2015), and the time it takes to control a cell depends on it. The added value of this paper is the strategy timing, as tracking the fire arrival and brigade arrival times allows for imposing some feasibility and safety constraints: a control cannot be placed in a cell in a certain moment if it is already burned or if the fire is too close for it to be safe. Moreover, it avoids the simultaneity of controls. However, this level of detail in the model implies that the running times are unaffordable, taking days to solve some cases and running out of memory for others. Moreover, it considers only one brigade and crossing a cell more than once is forbidden; these assumptions are not realistic since normally several teams are coordinated and the traveling paths are usually roads that can be used many times, as long as it is safe.

A different approach, albeit interesting to mention, is the one by **Homchaudhuri et al. (2013)**, who developed a simulation–optimization scheme. Fire spread, based on the Huygens principle, is simulated stochastically in heterogeneous terrain, implementing a wind–slope correction. Given predefined curves, the optimization module determines the starting points and parameters of the curves that the brigades follow to close the perimeter. It considers constant fire line production rate and that the starting point of one crew is the finishing point of another one. Then, fire suppression is simulated to determine the total area burned using the Monte Carlo method, assuming the worst scenario, and discarding solutions deemed unacceptable/infeasible. Fire propagation and suppression affect one another in an iterative way. The objective is to minimize the area enclosed by the curve if the fire is surrounded completely. This value is infinity if the fire escapes the enclosed area. A major limitation reported by the authors is that this is a completely data-driven method, whereas firefighting operations have a strong heuristic component based on expert knowledge, so a method which combines both would be more convenient.

In any case, the mentioned methodologies address detailed space information and entail an improvement over the ones in previous sections. Aside from considering the interaction between fire spread and suppression, these methodologies determine the final shape of the fire lines to be constructed, providing a more extensive and realistic suppression plan.

POD-Based Models

Another way of discretizing the space is using potential wildland fire operation delineations (PODs), which are the representation of areas that summarize risks and identify fire management opportunities (Thompson et al. 2016). This representation provides a tight relationship between the real landscape and the modeled grid, which uses terrain features such as rivers or roads as POD boundaries, grouping in each POD a piece of landscape with similar characteristics. This approach bridges the gap between OR techniques and decision makers, since it makes use of predefined PODs that are normally determined by managers.

This way of modeling the space is used by **Wei et al. (2018)**. They developed an MILP model to aggregate these structures into a response POD (rPOD) for containing large fires—a patch between PODs is created using adjacency relationships, where containment lines are established along the boundaries of the rPOD. Stochasticity is included by weather scenarios, in terms of wind speed and direction as well as fuel moisture. However, they do not consider spread probabilities nor the timing of line construction in relation to fire arrival times. Safety constraints are included to avoid fire suppression in places with flame length over a threshold, which is calculated using FlamMap. This approach, like in Belval et al. (2015), also considers beneficial fires, represented by positive conditional net value change (cNVC). Point protection is represented by avoided loss in terms of cNVC. The highlight of this model is that it considers both fire confinement and point protection in a joint manner, leveraging a more accurate space discretization such as PODs. However, it does not impose a limitation on the resources, and models the fire in a very simplistic way using adjacency rules, but not calculating arrival times. Thus, fire line construction times cannot be determined based on fire arrival.

Wei et al. (2019) built on Wei et al. (2018) to improve the development of rPODs considering fire spread probabilities and spread rates. This allows for determining the order in which the PODs are adhered to the rPOD within a set of periods, estimating fire arrival time to the boundary as the earliest. The time it takes to build a fire line is dependent on flame length. A second model to determine the timing of the suppression strategy is built, which takes as input the rPOD boundaries identified from the previous model and the set of points selected for point protection. This novel second optimization encourages the completion of containment line prior to fire arrival, avoiding firefighters being surrounded or endangered by the fire. The model improves on Wei et al. (2018), because it limits the number of crew hours to be used in each period; however, a major shortcoming is that it does not address fire line or point protection simultaneity within each period.

A limitation of the mentioned models is that a constructed fire line is assumed to hold once built; there is scarce study of system redundancy in fire suppression. Belval and Wei (2019) account for fire line quality construction in terms of the needed time for constructing the line for it to hold depending on fire intensity; however, it only forces this time to be enough, but does not consider line breaching.

In this regard, **Wei et al. (2021)** extended the models from Wei et al. (2018, 2019) to evaluate the effectiveness of contingency strategies under randomly generated scenarios through an MILP model. The goal is to study how redundant firelines may reduce uncertainties from stochastic fireline breaching. The minimum travel time algorithm (MTT) is used to dynamically track the fire arrival time to the centroid of each POD. The methodology tests four types of fireline construction to delineate rPODs, evaluating trade-offs between fire loss and suppression effort, finding that no contingency strategy could outperform the others in all random scenarios. Thus, fire managers may select different containment strategies based on their risk preference, resource costs, resource availability, or firefighter safety. Nevertheless, despite PODs being a good way of dividing the space based on terrain features, sometimes they are too large for tracking fire spread using the MTT algorithm.

Other Models

Chan et al. (2020) proposed an innovative approach for the resource allocation problem during fire suppression. In order to cope with the uncertainty, the authors developed a strategy in three phases called "Firefly". First, a set coverage problem is identified, which maximizes the area explored by a number of deployed drones. Solved by a greedy algorithm, the solution provides information of how the fire is developing and about the utility of the surveilled cells. In some cases, the first phase is not able to develop a plan to watch over all the cells given the available drones, so a second phase estimates the utility of the cells not assessed. Third, a knapsack problem is solved to maximize the utility of the chosen areas where the brigades are going to be dispatched to, modeling the space as a graph.

Rodríguez-Veiga et al. (2018) proposed two linear integer programming models to solve two different decision problems related to the allocation of aerial resources, wherein flying routes should be optimized and monitored to avoid and reduce the risk of collision. The first model is designed to maximize the output per hour of aerial resources flight time, and the second manages the allocation of aerial resources to refueling bases. The first one should be run each time a new aerial resource enters or abandons the extinguishing protocol. It uses stochasticity due to the uncertainty in the efficiency of aerial resources during a wildfire. The second model is executed after the coordinator determines when and where each aircraft would run out of fuel. This one is deterministic due to the nature of the parameters involved.

Despite all the efforts to construct fire lines capable of holding the fire, sometimes they are not sufficient, and the fire finally escapes, endangering lives, assets, and infrastructure. Although it is out of the scope of this paper, it is important to mention that OR is also useful in optimizing the operations related with asset protection (Van Der Merwe et al. 2015; Roozbeh et al. 2018) and evacuation Shahparvari et al. (2019).

Preparedness and Response: Combined Approaches

Haight and Fried (2007) presented a two-stage stochastic MILP model for the deployment of resources called standard response model (SRM). Scenarios are created using CFES2, which represent the daily number, location, and intensity of the fires. For each fire the standard response required is calculated as the “desired number of resources that can reach the fire within a specified response time”. This will measure whether a fire can be contained and how much effort is required to do it, or whether the fire will escape. Two objectives are minimized in the objective function: the number of suppression resources deployed and the expected daily number of fires not receiving a standard response. The authors also create a heuristic approach based on CFES2 to compare the results with the MILP model. The strength of the scenario-based SRM is its tractability and integration of expert knowledge through the definition of standard response. However, the model does not estimate the number of escaped wildfires, nor models fire containment. Moreover, exogenously generated dispatch rules assume a perfect knowledge of the resources needed to define the standard response, which is a very specific assumption that does not hold in reality.

Based on Haight and Fried (2007), **Yohan et al. (2014)** developed a two-stage model for deployment and dispatch that minimizes the expected number of fires not receiving a predefined response. This response is also defined as the required number of resources that can reach the fire within a maximum time. They apply logic from the scenario optimization (scenarios are created via the fire simulation model from Byungdoo et al. (2011) and the maximal covering location framework. The first stage addresses the assignment of helicopters at the beginning of the fire season and the second determines their daily dispatch, assuming the rest of the resources are located at their bases. The major contribution of the paper is the utilization of GIS information to account for heterogeneities between the different areas to protect, considering priorities given the fire intensity.

Haight and Fried (2007), **Ntaimo et al. (2012)** improved the model considering that resources can be moved between their bases before a fire occurs. It also considers multiple types of fire-fighting resources with different production rates. The first stage minimizes fixed costs from renting and relocation. The second stage, based on the methodology by Donovan and Rideout (2003), minimizes the C+NVC of the burned area for each scenario, considering fires not receiving standard response. In this case, a fire is said to receive a standard response if the sum of all production rates is greater than a certain production rate. The output of the model is the number of contained fires and the expected number of escaped fires. Using rule-based dispatching poses a major improvement over Haight and Fried (2007), since it relaxes the assumption of the manager’s perfect knowledge of the resources needed. The set of scenarios is developed using BehavePlus as a fire simulator, which determines the standard response required by each fire. However, if too many scenarios are used the computing capacity is insufficient, so the authors propose a sampling method in order to solve it.

Another approach is followed by **Gallego Arrubla et al. (2014)**, developing a one-stage MILP model. The model includes stochasticity for resource pre-allocation, deployment, and dispatch of dozers. Combining a fire behavior simulator and a wildfire risk model (Texas Wildfire Risk Assessment system) with a probabilistically constrained stochastic MILP, they account for the risk-aversion of the fire manager, integrating expert knowledge. Following the line of Donovan and Rideout (2003), they also use the C+NVC to compute the cost associated with fire suppression, determining the number of contained fires and the wildfire risk associated with fires not receiving a standard response, along with the cost derived from damages and losses produced by the fire. Standard response is determined, as in Ntaimo et al. (2012), as the minimum standard production rate to be achieved for containment. A limitation of the model is that it only includes one type of resources with constant production rates, instead of combining the production rates from different types of firefighting resources.

A new contribution to the literature on initial attack planning can be found in a paper by Ntaimo et al. (2013), who do not consider the standard response required by each fire, but develop an explicit fire growth response model (EFGRM) which accounts for the fire behavior. Combining simulation and the two-stage

SRM by Ntaimo et al. (2012), the first instant in which fire is contained is determined. In this case, BehavePlus is used, for developing the fire scenarios and to calculate the fire perimeter each half an hour in a period of six hours. This allows for developing a more specific action plan on how to contain the fire and determining how much of the fire perimeter remains unattended. However, it is assumed that no explicit interaction between the fire perimeter and fire line construction exists. The results of the study demonstrate that the response time restriction imposed by the fire manager planning unit has a direct impact on the number of fires that can be contained.

Not considering costs directly, **Sakellariou et al. (2020)** developed a methodology with two modules, aimed at covering the maximum population served within the predefined time frame. The first module is directed at strategic planning. Two scenarios are considered, based on an ideal (10 min) and real (31 min) time response, to maximize the coverage and minimize the number of supply points, selected from candidate facility locations. Once the optimal locations have been determined, the second module assesses the response capabilities of moving vehicles via Dijkstra’s algorithm, to find the best routes from the supply to the demand points. A novelty of this paper is that it performs a second computation to determine an alternative route in case natural or artificial barriers arise. As well as for Suarez et al. (2016), arrival times are calculated considering the road network quality. The authors propose this second module to be used in real-time operations. The added value of this model lies in the fact that it deals with WUI fires considering operational and strategic efficiency in an integrated framework.

Another objective is explored by **Zhou and Erdogan (2019)**, minimizing the people at risk who need to be evacuated, minimizing also the total expected cost of hiring additional on-duty resources. To address the two objectives, goal programming is used. However, it may pose disadvantages since the assumptions made on goals and the priorities must be made by the decision-maker and are difficult to determine. The MILP model has two stages and addresses fires in the WUI interface as Sakellariou et al. (2020). The main improvement, compared to the previous deployment and dispatch models, is that the fire behavior is simulated within the model, similarly to as in Wei et al. (2011) and Alvelos (2018) or Belval et al. (2015, 2016), Belval and Wei (2019), accounting for the interaction between the fire and the suppression strategy. It is an integrated model that support decisions in resource acquisition and allocation before the fire starts, and decisions during the fire event regarding resource deployment and dispatch. Due to the growth in model size as the grid enlarges, the authors explore a novel approach to keep the number of variables constant by increasing the size of the grid for the scenarios.

Another approach can be found in **Wei et al. (2015)**, with a simulation–optimization methodology that also models the interaction between fire behavior and suppression. It is a two-stage stochastic model: suppression resources have to first be acquired and then deployed and dispatched for the season, ensuring they are sufficient for suppressing a series of scenarios. A chance-constrained approach is used, creating a deterministic equivalent formulation such that most fires have to be controlled via initial attack. The goal, once the resources have been acquired in the first stage, is trying to put the fires out as soon as possible, considering their specific fire behavior. The perimeter growth is calculated with FARSITE, and suppression is performed by having a fire line construction rate higher than perimeter growth. A limitation of this model is that it does not consider changes in staff levels, or relocation; moreover, resources are assumed to attend one fire per day and then return to their bases.

This model is further improved by Wei et al. (2015) by including a post-optimization procedure to assess the solution and refine it to determine final solutions. In addition, it includes endogenously designed dispatch rules into resources acquisition and deployment decisions, which is the main contribution of this paper. However, it still assumes that the manager could anticipate the fire locations and their features before creating the dispatch plan for each day. Moreover, a major issue remains unresolved and is that resources are limited to be dispatched to only one fire per day. Tracking the first hour a fire is contained could allow for releasing the resources engaged in that fire and redeploying them to other fires in the same fire day.

All these models have proved useful in integrating into a single model two of the fire suppression stages described in Martell (1982). However, as not only two, but all the stages are interrelated, skipping just one of them may result in suboptimal solutions, so further studies to test the utility of multistage systems may be justified by Wei et al. (2015).

All the above-described models are based on optimization techniques from mathematical programming, and although the theoretical study of the fire-fighter problem (FFP) has given rise to interesting discussion, the focus of this review is on the papers discussing procedures that support decision-making in real situations. Moreover, some of the models are not able to solve real instances because they rely on commercial solvers that do not provide solutions for large instances.

2.2.2.3 Assessment of relevant models

A summary assessment of models related to strategies or methodologies for resource deployment and management to mitigate forest wildfires is provided in appendix 5.2 (Table 45).

2.2.3 Relevant tools

2.2.3.1 Overview of relevant tools

Table 2 provides an overview of tools that are used for resource deployment and management against forest wildfires.

Table 2: Overview of tools used for resource deployment and management to mitigate forest wildfires.

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
T11.1	WiSE	Desktop and Mobile application, Android, iOS, Windows.	A, B	Tool designed to calculate safety zones and prevent burn injury to wildland firefighters.	Butler and Cohen (1998)
T11.2	fiRESPONSE	Windows application	B	An enterprise-wide incident management system providing capabilities for managing emergency response to all hazard incidents with an emphasis on wildfire risk.	Not specified.
T11.3	ArcGIS	Desktop and mobile application, Windows and Linux	A, B	Full-featured professional GIS application. Licence required.	GIS
T11.4	Fire Incident Dashboard	Requires ArcGIS Online; ArcGIS Pro 2.9 or later (Basic,	A, B	Visualizes fire and emergency medical service	GIS capabilities

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
		Standard, or Advanced).		(EMS) incidents sourced from computer-aided dispatch or records management systems and monitor associated response times	
T11.5	QGIS	Desktop and mobile application, Windows and Linux.	A, B	Free license full-featured professional GIS application.	GIS
T11.6	StreetWise	Desktop and Mobile application, compatible with Android and iOS.	B		Not specified.
T11.7	GINA	Desktop and Mobile application, Windows.	A, B	Provides dispatching, navigation, vehicle tracking, data transfer, mapping.	Not specified.
T11.8	CoordCom	Desktop and Mobile application, Windows.	A, B	System for management and coordination of professional firefighters in Slovakia.	Not specified.
T11.9	Google Earth	Desktop and mobile application, Windows and Linux, compatible with Android and iOS.	A, B	3D representation of Earth based primarily on satellite imagery, providing a series of other tools through the desktop application, including a measure distance tool. Freeware.	Not specified.
T11.10	WFDSS	Desktop and Web based application.	A, B	Allows fire managers and analysts to accurately document their	Not specified.

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
				decision-making process by allowing results of analyses to be attached to the decision point and included in the final incident report.	
T11.11	SSDE	Web based application, Earth Engine App.	B	Integrates evolving science and large scale, high resolution georeferenced data to calculate landscape scale safe zone size, shape, and location estimates.	Campbell et al. (2022)

2.2.3.2 Description of relevant tools

Wildfire Safety Evaluator (WiSE)

WiSE is a tool designed to provide safe separation distance calculations to wildland firefighters. This new tool gives firefighters the crucial ability to identify suitable safety zones while in the field. With inputs based on direct observations in the field, wildland firefighters now have the ability to quickly calculate the distance needed to provide themselves and others, safety from burn injury. wildland firefighters can enter on-scene observed data via parameters such as: Wind, Slope, Fuel Height and Resource Information. Using these inputs, the individual can quickly calculate their Safe Separation Distance (SSD) and view the results on a map. As conditions change, wildland firefighters can quickly update observed conditions to view updated results, all without having to leave the mapping screen. WiSE is unique in that it does not require an active data connection to calculate these safety zones. (WISE 2018)

The Butler and Cohen (1998) model is integrated in the system to calculated the safety zones.

WiSE has been developed to work across multiple devices, both mobile and desktop. Download WiSE for Android, iOS, and Windows operating systems. Android and iOS versions are available through the Google Play and Apple App stores. (WISE 2018)

To facilitate learning, the WiSE website has an interactive mapping application where users can upload their safety zones to share with other users. This safety zone repository provides users the ability to review other safety zones providing a mechanism to learn and benefit from the user community. The web data repository only includes those safety zones that WiSE mobile users choose to upload and share. Participation is optional. (WISE 2018)

fiRESPONSE

The fiRESPONSE software is designed to support the entire lifecycle of an incident delivering a common operating picture that allows multi-agency use with seamless synchronization and data sharing between different users, agencies, and devices through multiple platforms. Its core capabilities are built for incident management, resource management, & real-time resource tracking through spatially enabled platforms designed to enhance situational awareness & support operational activities. (TECHNOSYLVA 2023)

Incident Management allows managing incidents from declaration to control with robust tools for defining, reporting, mapping and tracking incidents. Situational Awareness serves for providing decision makers and operational staff real-time situational awareness on multiple platforms. Resource Management provides a comprehensive application for inventory & personnel management, resource activation, and resource scheduling and rostering. Resource Tracking is used for real-time tracking of resources using AVL, AFF and GPS capabilities to support resource allocation and firefighter safety. (TECHNOSYLVA 2023)

fiResponse™ includes additional modules and applications that support specific agency business workflows for final fire reporting, burn permit authorizations, suppression billing, and daily fire danger analysis. It can be used as a stand-alone solution, or in conjunction with WFA-E for added situational awareness and risk assessment. (TECHNOSYLVA 2023)

ArcGIS

ArcGIS is a full-featured professional desktop GIS application from Esri. With ArcGIS user can explore, visualize, and analyze data; create 2D maps and 3D scenes; and share his/her work to ArcGIS Online or your ArcGIS Enterprise portal. (ESRI 2023)

ArcGIS provides dynamic maps and GIS tools to identify wildfire risks and craft mitigation strategies. During fires, mobile data collection tools and map-based dashboards with live data supports the decision-making process of relevant authorities (incident commanders, forest managers, civil protection workers, etc.). It is applicable as in preparedness as in mitigation and monitoring phase.

Further, there are introduced the possibilities for using ArcGIS for complex analysis.

Response Time Modeling Utilizing a fire station layer and a street layer, response time analysis can be performed. A street layer is often represented in GIS as a series of lines that intersect on the map, creating a GIS network. Each street line segment between intersections can contain the road type, distance, and travel speeds (miles or kilometers per hour) permitted in the underlying data within the GIS system. This allows users to identify a station location, specify a travel time, and run a network analysis. The result will be illustrated by an irregular polygon around the station that closely approximates where a fire apparatus could travel in any direction for the specified time. This type of analysis could be performed simultaneously on all the department's stations to analyze gaps in coverage, run orders, and so forth. (ESRI 2006)

Incident trend analysis is also a common practice by fire departments. With GIS, incident trend analysis can be performed quickly with all the relevant information. GIS can access and "geocode" (place a point on the map) historical incidents. This capability can be refined by conducting a spatial query to the records management database that specifies the type of incident, time range, or specific geographic area. For example, a GIS user could request to see arson fires that occur between the hours of 1:00 a.m. and 5:00 a.m. on Saturdays in fire districts 1 and 2. GIS will interrogate the records database and place points on the map that meet this request. The GIS user can access all the information concerning each incident by simply clicking on the incident point. GIS can add additional information by displaying the demographics for each of the two fire districts identified in the spatial request. (ESRI 2006)

Event modeling allows the user to identify a location (factory, hazardous material location, rail track intersection, etc.), place a point on the map, and run a selected model. Models could be anything from plume dispersion to an explosion. GIS can display the model on the map; delineate various levels of danger; and identify exclusion zones, infrastructure damage, and population effects. In addition, road closure requirements, safe routes into and out of the hazardous area, and appropriate hospitals that could quickly service the emergency can be displayed along with other information for emergency decision support. Modeling can be used for analyzing vulnerabilities, preplan development, training, or communicating with the public and policy makers. (ESRI 2006)

GIS can become a central repository for a variety of nonspatial data. Nonspatial data, such as floor plans (computer-aided design drawings), photographs, preplans, and other documents, can be linked to features on the map (documents or photos that pertain to a particular building location or other actual feature location). This information, when configured with mobile computers, can provide first responders with information essential when sizing up for deployment. Historically, GIS required having software and data on a computer with a trained GIS technician. Today, newer GIS application software has evolved and can operate effectively in a networked or Web-based environment. GIS software can reside on a Web server, the GIS data can be in several different locations or other Web servers, and users can access the GIS application through a Web browser. Web-based GIS services make it possible to deploy regional GIS applications and dramatically reduce costs and maintenance. GIS is rapidly becoming a standard technology for many industries. (ESRI 2006)

Dispatchers have an important responsibility to process emergency calls and send the appropriate public safety resources to the emergency location based on the type and urgency of the incident. GIS is an important component of the dispatch system. Dispatch systems or computer-aided dispatch (CAD) systems typically contain a file GIS can become a central repository for a variety of nonspatial data. Nonspatial data, such as floor plans (computer-aided design drawings), photographs, preplans, and other documents, can be linked to features on the map (documents or photos that pertain to a particular building location or other actual feature location). This information, when configured with mobile computers, can provide first responders with information essential when sizing up for deployment. Historically, GIS required having software and data on a computer with a trained GIS technician. Today, newer GIS application software has evolved and can operate effectively in a networked or Web-based environment. GIS software can reside on a Web server, the GIS data can be in several different locations or other Web servers, and users can access the GIS application through a Web browser. Web-based GIS services make it possible to deploy regional GIS applications and dramatically reduce costs and maintenance. GIS is rapidly becoming a standard technology for many industries. The remainder of this section will examine how GIS can be and is being used in all aspects of fire and emergency services. Computer-Aided Dispatch Dispatchers have an important responsibility to process emergency calls and send the appropriate public safety resources to the emergency location based on the type and urgency of the incident. GIS is an important component of the dispatch system. Dispatch systems or computer-aided dispatch (CAD) systems typically contain a file called the Master Street Address Guide (MSAG). This file contains street address information and service areas for the jurisdiction that the dispatch center services. As emergency calls are received, they may be accompanied with address information from the telephone company's emergency phone record database. This address is entered or electronically transferred to the CAD system, which compares it to the MSAG. When the address is matched, the specific service area is also identified with the specific units that should be dispatched to the emergency. If the telephone company does not provide a digital address with the call, dispatchers must obtain it from the caller and type it into the system. Many computer-aided dispatch systems have begun to integrate GIS technology. GIS takes the address and automatically geocodes the incident and displays it on a map. There are several benefits of having the incident displayed on a GIS map. New calls reporting the emergency may have different addresses but are reporting the same incident that was previously recorded. The GIS map display will illustrate that even though it is a different address, it is in the same proximity as the original call. (ESRI 2006)

Wildfire planning and analysis, suppression methods, fire prevention and education, and vegetation management techniques continue to evolve and change through information management technologies. GIS is one of the primary technologies influencing these changes. (ESRI 2006)

Fire Incident Dashboard

Fire Incident Dashboard can be used to visualize fire and emergency medical service (EMS) incidents sourced from computer-aided dispatch or records management systems and monitor associated response times. It improves operational visibility for supervisors in a fire service agency and allows them to rapidly identify emerging incident patterns and diagnose response problems. This increased operational awareness ensures accreditation standards are being met and community safety standards are satisfied. Fire Incident Dashboard is typically implemented by fire service agencies that want to proactively monitor response times and detect incident patterns quickly. To work with, it requires the following: ArcGIS Online or ArcGIS Pro 2.9 or later (Basic, Standard, or Advanced). (ArcGIS Solutions 2023)

The Fire Incident Dashboard solution delivers a set of capabilities that help users source incident records from computer-aided dispatch or records management systems, visualize fire and EMS incidents, and monitor trends or patterns. (ArcGIS Solutions 2023)

QGIS

QGIS is a user friendly Open Source Geographic Information System (GIS) licensed under the GNU General Public License. QGIS is an official project of the Open Source Geospatial Foundation (OSGeo). It runs on Linux, Unix, Mac OSX, Windows and Android and supports numerous vector, raster, and database formats and functionalities. It provides a continuously growing number of capabilities provided by core functions and plugins. Users can visualize, manage, edit, analyze data, and compose printable maps. (QGIS 2023).

QGIS is not only a desktop GIS but also a spatial file browser, a server application, and web applications. Its capabilities and tools are very similar to those provided in ArcGIS products.

StreetWise

StreetWise CADlink is real software for fire departments that are serious about getting the most from tablet computers or replacing clunky and expensive laptops. They can use it as a standalone MDT, integrate it to their Emergency Reporting® NFIRS report, and then even have bi-directional interfaces are available for sharing AVL and status buttons back to many CAD systems. With regional options, StreetWise allows users to seamlessly share AVL, hydrant locations, preplans and more with your mutual and auto-aid partners so all responding units are truly part of the same team. (StreetWise 2023)

Among the features of the system belong: instant call updates, mapping and navigation, status buttons for precise performance statistics, live AVL/vehicle tracking with regional options, 2-way CAD integration options for status changes and dispatcher AVL, hydrant location and attributes display, instant shared map customization with regional options, incident-specific tactical command and control functions, instant incident photo sharing for situational awareness, total NFPA 1620 preplan collection, management and display, integration with Emergency Reporting, web database portal providing easy access to all data, canned reports, custom reports and analytics, detailed training video library, 24-hour support. (StreetWise 2023)

GINA

There are available four options: GINA Central, GINA Tablet, GINA Hems and GINA GO.

GINA Central, in case of an emergency, serves for dispatching and navigating units in the area, establishing real-time communication channels, and ensure protection and safety of intervening personnel. This product provides: dispatching; GPS location in real time; shortest navigation to a place; task management and routing; reports from the field about its implementation progress; data and information sharing; built-in map functions (drawing, icons, multimedia); geographical and analytical functions (filters, “heat” maps, etc.). (3MON 2023a)

GINA TABLET Connect all units of the integrated rescue system for a faster arrival time to the incident site. The system communicates with the 112 operation center (security number) and provides commanders with a tool for more efficient management of activities and correct decision-making in each phase of the intervention. (3MON 2023b)

The tablet can be used during the journey to the intervention (list of exits, statuses, navigation), during the intervention itself (mutual coordination, drawing on the map, creation of photos and their sharing) and also after the intervention (photo archive, data storage, visualization of the route to the intervention).

Installation in vehicles takes about 30 minutes and there is no need to interfere with the interior of the vehicle. Simply attach the durable mount to the dashboard and you're ready to go. (3MON 2023b)

While driving the fire officers are allowed: immediate receipt of departure order; sending statuses with confirmation; sending independent of the radio signal; real-time location tracking for all units; navigation; current traffic situation; possibility of calling the reporter directly. (3MON 2023b)

On Incident site, it provides: mutual coordination of the arrival of units; possibility to create, edit and share photos; sharing map previews and drawing on maps; points of interest "POI" overview; access to building evacuation plans; operational building cards. (3MON 2023)

Among advanced features provided by GINA Tablet belong: meteorological radar; video streaming from portable cameras; communication via messages; drone mapping support; loading data from documents with the possibility of person lustration; dark mode. (3MON 2023b)

GINA HEMS is an application designed to help air rescuers. The system communicates with the operations center and provides pilots and crew technicians with tools for intervention management and correct decision-making in all phases of flight. Extensive installation in the helicopter is not required, the system is certified for aviation use. It provides following features in flight: real-time position and ETA (3, 5, 10 min.); online emergency update; coordination with other interested units; six map bases; map base based on zoom level (terrain – buildings – orthophoto); integrated flight operations; integrated meteorological radar; messenger for quick communication with other units and the operations center; offline search engine. (3MON 2023c)

GINA GO is a localization application for increasing safety and collecting data from the field. It is available for Android, iOS and can be combined with Black Berry mobile phones. The app uses your phone's internet connection (4G/3G/2G/EDGE or WIFI) to share personnel location and send an SOS signal to your operator or selected recipients. (3MON 2023d)

Two tracking modes can be used in the application. Private mode is the best compromise between power consumption and personal security, as location is approximate and hidden unless person is in danger. Safety mode shares location in real time and is the best choice for team coordination and movement tracking. (3MON 2023d)

GINA GO can also be used to collect data from the field. Generated reports with detailed information from the field are sorted into folders in the application in such a way that provide immediate access to them. (3MON 2023d)

GINA Central and Tablet are used for fire and rescue service forces and resources management and coordination as well as volunteer fire fighters mostly in the Czech Republic, used only at the Fire and Rescue Service of the Slovak Republic.

CoordCom

CoordCom is a product of Eriksson company. It is an integrated system for coordination of forces and resources of the Integrated Rescue System (including firefighters). It is a closed system, available for fire and rescue service forces and resources management and coordination and only in the Slovak Republic. It is administrated by the Ministry of Interior of the Slovak Republic.

It provides database with forces and resources of the Fire and Rescue System, GIS module with localization of a person calling to the emergency links 112, 150; module to create and store Incident Report, database of all instruction for fire brigades, list of dangerous substances together with their properties.

Google Earth

Google Earth is a computer program that renders a 3D representation of Earth based primarily on satellite imagery. The program maps the Earth by superimposing satellite images, aerial photography, and GIS data onto a 3D globe, allowing users to see cities and landscapes from various angles. Users can explore the globe by entering addresses and coordinates, or by using a keyboard or mouse. The program can also be downloaded on a smartphone or tablet, using a touch screen or stylus to navigate. Users may use the program to add their own data using Keyhole Markup Language and upload them through various sources, such as forums or blogs. Google Earth is able to show various kinds of images overlaid on the surface of the Earth and is also a Web Map Service client. In 2019, Google revealed that Google Earth now covers more than 97 percent of the world, and has captured 10 million miles of Street View imagery. (Wikipedia)

In addition to Earth navigation, Google Earth provides a series of other tools through the desktop application, including a measure distance tool. Other features allow users to view photos from various places uploaded to Panoramio, information provided by Wikipedia on some locations, and Street View imagery. (Wikipedia)

Google Earth's imagery is displayed on a digital globe, which displays the planet's surface using a single composited image from a far distance. After zooming in far enough, the imagery transitions into different imagery of the same area with finer detail, which varies in date and time from one area to the next. The imagery is retrieved from satellites or aircraft. (Wikipedia)

As an example, there is introduced, by the US Forest Service developed, a new tool to capture accurate real-time data in an easy-to-use application that is accessible to a larger group of users in a timely fashion. The tool, called the “Automated Flight Following” system (AFF), consolidates data transmitted by GPS devices on Forest Service and contracted airplanes and displays their real-time location in Google Earth. Other relevant GIS data created with ESRI can also be imported into the AFF system. For example, the Forest Service gets regularly updated shape files of temporary flight restrictions from the Federal Aviation Administration (FAA) and displays those in AFF as 3-D objects. Weather, road, and fire perimeter information from other agencies is similarly imported into AFF providing a comprehensive situational awareness view to a broad group of Forest Service employees and cooperators. (Roth 2008)

In Slovakia, it is used by firefighters (professional as volunteer) for creation of graphical layers representing the incident site, location of forces and resources deployed, potential fire spread.

Wildland Fire Decision Support System (WFDSS)

WFDSS combines desktop applications for fire modeling into a web-based system for easier data acquisition. It provides an easy way for fire managers and analysts to accurately document their decision-making process by allowing results of analyses to be attached to the decision point and included in the final incident report. It also provides one decision process and documentation system for all types of wildland fires. Is a web-based application for easier sharing of analyses and reports across all levels of the federal wildland fire organization. Introduces economic principles into the fire decision process. (WFDSS 2023)

This system assists fire managers and analysts in making strategic and tactical decisions for fire incidents. It has replaced the WFSA (Wildland Fire Situation Analysis), Wildland Fire Implementation Plan (WFIP), and Long-Term Implementation Plan (LTIP) processes with a single process that is easier to use, more intuitive, linear, scalable, and progressively responsive to changing fire complexity. (WFDSS 2023)

WFDSS integrates the various applications used to manage incidents into a single system, which streamlines the analysis and reporting processes. (WFDSS 2023)

WFDSS follows an analytic deliberative process for decision making. Risk-informed decision making requires two distinct but linked processes: analysis and deliberation. Analysis involves the rigorous, replicable methods to provide information about factual questions. While analysis brings new information into the decision making process, it informs the deliberation. Deliberation is the discussion, reflection, and persuasion to communicate, raise issues, collectively consider issues, increase understanding, and facilitate substantive decisions. New analyses are framed as deliberation brings new insights, questions, and problem formulation. (WFDSS 2023)

Safe Separation Distance Evaluator (SSDE)

SSDE represents a new, interactive, web-based, open-access mapping tool for estimating safe separation distance (SSD) and evaluating potential safety zone (SZ) effectiveness through geospatial analysis. Instead of relying on lidar, this tool uses LANDFIRE Existing Vegetation Height data, which is both nationally available in the contiguous US and is updated every few years. Additionally, instead of only assessing SSD-driven suitability on clearings that already exist, this tool allows users to draw their own SZ polygon to evaluate the potential suitability of a SZ in any environment. Since LANDFIRE vegetation heights may not be as accurate as airborne lidar, given that it is a modeled product driven by satellite imagery, it is important to quantify the effects of differing sources of vegetation height data on SSD evaluation. (Campbell et al. 2022)

The Safe Separation Distance Evaluator (SSDE) algorithm (Campbell et al. 2022) is built and applied in Google Earth Engine (GEE), a cloud-based platform for processing and analyzing GIS and remotely sensed data, using the JavaScript application programing interface. GEE was selected for few reasons: (1) it enables the production of user-facing applications that can be widely accessed by anyone with an internet connection; (2) it hosts an immense catalog of geospatial data, including datasets necessary for the analysis of SZ suitability; (3) its cloud computing capabilities provide for rapid execution of complex geospatial functions, allowing users to quickly assess SZ suitability (Campbell et al. 2022). The model by (Campbell et al. 2022) has already been described in chapter 2.2.2.

SSDE is not currently intended to be a real-time decision-making tool for firefighters on the ground.

2.2.3.3 Assessment of relevant tools

A summary assessment of existing tools used for resource deployment and management to mitigate forest wildfires is provided in appendix 5.2 (Table 46).

2.3 M21: Fire behavior models

2.3.1 Introduction

Wildfires have become a major research subject among the national and international research community. Different simulation models have been developed to prevent this phenomenon. Nevertheless, fire propagation models are, until now, challenging due to the complexity of physics and chemistry, high computational requirements to solve physical models, and the difficulty defining the input parameters.

According to Sullivan (2017), the simulation of wildfires remains a challenging and complex task because it involves both multi-physics and multi-scale. Wildfires can be described as a complex combination of highly chaotic chemical reactions and physical processes. The transport of the energy released due to the chemical reactions occurs at scales ranging from a few tens of meters up to several kilometers as a flame zone that self-propagates into unburnt fuel. Advection, radiation, and transport of burning material are the phenomena involved in energy propagation. Hence, due to the extremely complex phenomenon, its prediction is essential in decision-making for preventing and fighting a forest fire. An important parameter in wildfires is the rate of spread (ROS) which is a function of complex interactions between combustion, air flow, and atmospheric conditions. These interactions depend on the fuel (type, composition, and quantity), terrain (slope), and atmospheric conditions (mainly wind). The variability nature of these parameters complicates the task of accurately predicting the behavior and spread of wildfires.

There are three main categories of models for wildfire spread behavior across the landscape: physical and quasi-physical models, empirical and quasi-empirical models, and simulation and mathematical analog models. From this perspective, models of a physical nature are based on the fundamental chemistry and physics of combustion and fire spread, while the quasi-physical model attempts to represent only the physics. In turn, an empirical model contains no physical source, and it is generally based only on a statistical nature. In contrast, a quasi-empirical model uses some form of physical framework upon which to base the statistical modeling chosen. Lastly, simulation models implement the preceding types of models in a simulation rather than a modeling context, while mathematical analog models utilize a mathematical percept to model the spread of wildland fire. (Silva et al. 2022)

Bakhshaii and Johnson (2019), in their recent review, called these last two models a first-generation type of wildfire models. The authors also introduced the concept of a new generation of wildfire models that rely on the use of both physical and empirical fire models coupled with a numerical weather prediction model or computational fluid dynamic (CFD) model. However, despite all of the categories mentioned, it is possible in a simple way to classify the wildfire models into just two types in order to simulate the dynamic spatial fire spread across the landscape.

The first one is made of models based on CFD principles, which attempt to replicate fire behavior based on the fundamentals of fire, combustion, and heat transfer processes. CFD models are based on Navier–Stokes equations with auxiliary relationships for aspects such as chemical reactions, turbulence, and heat transfer. As a result, such models are less reliant upon extensive experimental relations for robustness. FIRETEC-HIGRAD model (Linn 1997; Linn, Cunningham 2005), developed at the Los Alamos National Laboratory, USA, is an example of a developed model based on the basic principles of CFD. This model consists of a coupled multiphase transport/wildlfire model based on mass, momentum, and energy conservation equations (HIGRAD), see Reisner et al. 1998; Reisner et al. 2000. This model is used to solve the equation of the local atmosphere motions, employing a fully compressible gas transport formulation in order to represent the coupled interactions of the combustion, fluid mechanics, and heat transfer involved in wildfires across the landscape. The wildfire propagation is based on the FIRETEC fire model.

The second one encompasses fire perimeter propagation models, which apply empirical equations for the ROS, such as the Rothermel model (Rothermel 1972), to simulate the fire perimeter's propagation. Fire perimeter propagation models are used to simulate the large-scale propagation of fire across a landscape rather than directly solve the physics and chemical fundamentals that govern the fire. They can be based mainly on empirical relationships measured in the field or based on mathematical expressions. The fire perimeter in these models is the interface between burnt, burning, and unburnt regions and can be subdivided into front-tracking methods or cellular methods. In the front-tracking approach, the fire perimeter is described as a set of lines that expand according to a given rate of spread, and the point source for future propagation is each point on the fire perimeter. These models are considered computationally fast, although only one type of front shape is usually considered, elliptical. Models using this approach include, among others, Phoenix RapidFire (Tolhurst 2008), Prometheus (Tymstra et al. 2010), Aurora (Johnston et al. 2008), and FARSITE (Finney 1998).

In the cellular category methods, the domain is discretized into a grid over which all input data are prescribed, all calculations are performed, and empirical or physical formulas are used to update the state of the grid (e.g., according to wind direction, intensity and also the vegetation) over time. Examples of such models include, among others, FireStation (Lopes et al. 2002) and FIREMAP (Vasconcelos, Guertin 1992). Although cell-based simulators are simpler to implement, they are not widely used in comparison with front propagation models due to the fire shape distortion caused by the restriction of fire travel between adjacent cells (Johnston et al. 2008).

Furthermore, there are two other models that play a major role in the assessment of wildfire data in the literature which are the mathematical models and the geographic information system (GIS). Mathematical models describe a system that makes use of language and mathematical concepts to describe a given phenomenon, such as the fire rate of spread. The importance of this type of model lies in the fact that they serve as a basis for developing various software programs that simulate the spread of fire in various configurations of terrain and environment, such as BEHAVEPlus (Andrews et al. 2008) and FARSITE (Mollina-Terrén et al. 2006) or FlamMap (Finney, 2006). The GIS model aims to store, display, and process spatial data. These data are stored in a grid structure (array) where each cell corresponds to a uniform parcel (Vasconcelos, Guertin 1992). Then, these models are combined with mathematical models to compute the fire spread.

There was further provided an overview of existing models and tools used for wildfire behaviour study, i.e. fire spread modelling and simulation. Among the literature sources belong also the scientific publications registered in the following databases: Scopus, Science Direct, Web of Science, Springer Link, and Science Open databases. The multiple keywords were used to find the most relevant literature sources. The documents were identified with advanced search query strings such as "(Fire spread rate OR Fire spread OR Fire propagation) AND (Wildfire OR Forest fire OR Wildland fire) AND (Mathematical model OR Modeling OR Simulation)". The different keywords used were based on the various subjects that characterize the main research object.

2.3.2 Relevant models

2.3.2.1 Overview of relevant models

Table 3 provides an overview of fire behavior models.

Table 3: Overview of fire behavior models.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M21.1	Rothermel (1972)	Mathematical; Semi-empirical	A; B	Surface fire spread, Rate of Spread (RoS), fire intensity, flame height	Can predict surface fire rate of spread. Sensitive in the accuracy of measurements of wind and in the accuracy of fuel description and fuel volume and moisture content specification.
M21.2	Byram (1959)	Mathematical	A; B	Surface fire	Can predict Fireline Intensity (I) and Flame Length (FL)
M21.3	Albini (1976)	Mathematical	A; B	Surface fire	Can predict Fireline Intensity (I) and Flame Length (FL)
M21.4	Anderson (1969)	Mathematical	A; B	Surface fire	Can predict flame residence time
M21.5	Van Wagner (1977)	Empirical	A; B	Crown fire	Can estimate critical surface intensity needed for transition from surface to crown fire. Can estimate critical crown fire rate of spread, needed for an active crown fire.
M21.6	Rothermel (1991)	Empirical	A; B	Rate of spread, fireline intensity, flame length, energy release, power, fire model, crown fire, fire size	Can predict crown fire rate of spread. Relevant to WUI dynamics.
M21.7	Thomas (1963)	Mathematical	A; B	Crown fire	Can predict crown fire flame length

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M21.8	Albini (1979)	Mathematical	A; B	Crown fire	Can predict spotting distance from torching trees
M21.9	Chase (1981)	Mathematical	A; B	Crown fire	Can predict spotting distance from torching trees
M21.10	Albini (1981)	Mathematical	A; B	Surface fire	Can predict spotting distance from a burning pile
M21.11	Albini (1983a, 1983b)	Mathematical	A	Surface fire	Can predict spotting distance from a wind-driven surface fire
M21.12	Chase (1984)	Mathematical	A; B	Surface fire	Can predict spotting distance from a wind-driven surface fire
M21.13	Morton (1965)	Mathematical	A; B	Fire plumes	Modelling fire plumes
M21.14	Morris (1987)	Mathematical	A; B	Spotting fires	Wind-driven spotting fires
M21.15	Albini et al. (2012)	Mathematical	A; B	Spotting distance, crown fire	Modeling maximum spotting distance
M21.16	Butler et al. (2004)	Mathematical	A; B	Crown fire	Can estimate crown fire intensity if the height of the flame above the canopy top
M21.17	Canadian Forest Fire Behavior Prediction System	Empirical	A; B	Rate of Spread, fire intensity.	Provides quantitative estimates of potential head fire spread rate, fuel consumption, and fire intensity, as well as fire descriptions. With the aid of an elliptical fire growth model, the FBP system gives estimates of fire area, perimeter, perimeter growth rate, and fire behavior at the head, flanks, and back of a fire.
M21.18	Cruz et al. (2003)	Mathematical	A; B	Crown fire.	Model of a crown fire based on data on crown fuel data (canopy base height; canopy bulk density).

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M21.19	Coen et al. (2013)	Mathematical	A; B	Surface fire	Model of surface fire behavior in relation to weather conditions
M21.20	Bogdos and Manolakos (2013)	Mathematical	A; B	Surface fire	Model used for fire spread modelling. Allows wind driven fire propagation.
M21.21	Linn, R. (1997)	CFD model / physical model	A; B	Surface fire, grassland fire spreading.	This model is used to solve the equation of the local atmosphere motions, employing a fully compressible gas transport formulation in order to represent the coupled interactions of the combustion, fluid mechanics, and heat transfer involved in wildland fires across the landscape. Another last phenomenon which is integrated is wildfire propagation.
M21.22	CFD (Computational Fluid Dynamics) model	Physical model	A; B	Surface fire, single tree burning, fire spreading.	This model is used to solve the equation of the local atmosphere motions, employing a fully compressible gas transport formulation in order to represent the coupled interactions of the combustion, fluid mechanics, and heat transfer involved in wildland fires across the landscape.
M21.23	Vasconcelos, Guertin (1992)	GIS based	A; B	Surface fire, fire spreading	Raster-based model, where the fire is modeled using a raster grid of cells with the status being burnt, burning, or unburnt. This technique considers the spread of the fire as a group of cell-to-cell interactions instead of considering the dissemination of a contiguous front.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Keywords	Capabilities / Restrictions of the Model
M21.24	Scott and Reinhardt (2001)	Mathematical	A;B	Crown fire	Forest fire behavior simulations, from a low-intensity surface fire to a high-intensity active crown fire.

2.3.2.2 Description of relevant models

Rothermel (1972) developed a mathematical model of fire spread offering a method for making quantitative evaluations of both rate of spread and fire intensity in fuels. Fuel and weather parameters measurable in the field are featured as inputs to the model. This model is based on the steady-state fire conditions. This mathematical model has been developed for predicting rate of spread and intensity in a continuous stratum of fuel that is contiguous to the ground. The initial growth of a forest fire occurs in the surface fuels (fuels that are supported within 6 feet or less of the ground). Under favorable burning conditions, if sufficient heat is generated, the fire can grow vertically into the treetops causing a crown fire to develop. The nature and mechanisms of heat transfer in a crown fire are considerably different than those for a ground fire. Therefore, this model is not applicable to crown fires. An exception can be made for brush fields. Brush, such as chamise, is characterized by many stems and foliage that are reasonably contiguous to the ground, making it suitable for modeling as a ground fire. Contributions to the spread of the fire by firebrands have not been included. Furthermore, the model has been designed to simulate a fire that has stabilized into a quasi-steady spread condition. Most fires begin from a single source and spread outward, growing in size and assuming an elliptical shape with the major axis in the direction most favorable to spread. When the fire is large enough so that the spread of any portion is independent of influences caused by the opposite side, it can be assumed to have stabilized into a line fire. A line fire behaves like a reaction wave with progress that is steady over time in uniform fuels. All input parameters can be determined from knowledge of the characteristics of fuels in the field. This does not imply that all the parameters of fuels and environment are readily available or can easily be measured. It does, however, delineate what parameters should be catalogued and eliminates those that are not needed. A convenient method of cataloguing input parameters is through the concept of fuel models tailored to the vegetation patterns found in the field. The companion fuel models are thus a set of input parameters that describe the inherited characteristics that have been found in certain fuel types in the past. The environmental parameters of wind, slope, and expected moisture changes may be superimposed on the fuel models. This fuel model concept has already been incorporated into the National Fire-Danger Rating System.

Byram (1959), in his work, described the general principles combustion process, hence the discussion on the combustion of fuels must necessary include forest fire behavior. Further he also described the factors affecting the rate of energy release: fuel moisture, wind, heat transfer, fuel size and arrangement, retardants and inhibitors. Then, he also described the “Fire Triangle”. He was also engaged with description of fuel-water relationship and combustion of forest fuel at all. Important outputs of his work represent the descriptions of the levels of fire intensity and mechanism of fire propagation.

Albini (1976) published a short course on fire behavior estimation. In his work, there are presented some theoretical and empirical relationships, along with computation aids, to be useful to those who are concerned wildfire behavior and effects. The purpose was to introduce fire behavior specialists to some toll developed and available that time and used for prediction fire behavior: Fire-Danger Rating, Fire Control, Prescribed Fire Planning. He described the capabilities and limitations of some of existing models, including the Rothermel`s model (1972) and also provided aids for the models in the form of Nomographs for Stylized Fuel Models.

Anderson (1969) published a work which was directed towards understanding and describing fire propagation through forest fuels and determining how the rate of fire spread is influenced by atmospheric, topographic, and fuel variables. In this work, there is introduced the development of mathematical description (moisture content, radiant heat, convective heat, bulk density of fuel bed, flame and burning characteristics) and test procedures and results, as well as provided comparison of own test results with those from other fire research.

Van Wagner (1977) proposed a theory, followed by a discussion of the local field evidence and comparison of the results with the previous published works on crown fires. The theory depends on three simple crown properties: height above ground, foliar bulk density, and foliar moisture content. It defines three classes of crown fire: passive, active and independent. The limiting criteria are critical levels of three properties of the fire itself: initial surface intensity, spread rate after crowning begins, a rate of forward heat transfer to the unburned crown fuel.

Rothermel (1991) provided method for predicting the spread rate, intensity, and size of expected crown fires. This method is based on a first approximation of the behavior of a running crown fire in fuels and weather conditions of the Northern Rocky Mountains in the Western United States. Rate of spread is developed from field data correlated to predictions of Rothermel's surface fire spread model. Energy release from surface fuels is obtained from Albini's burnout model. Fireline intensity is estimated from Byram's model. Flame lengths are estimated from Thomas' model. Energy rate, or power developed by the fire and ambient wind, is developed from Byram's equations and used to ascertain the possibility of a wind-driven or plume-dominated fire. The characteristics of these fires and dangers to fire fighters are discussed. A simple elliptical model is developed for estimating the area and perimeter of a large fire.

Thomas (1963) provided study focusing the size of flames from wildfires. He compared the flames produced by uncontrolled fires where the initial momentum of the fuel is low with the momentum produced by buoyancy. The heights of such flames with wood as the fuel were examined and discussed in terms of both a dimensional analysis and the entrainment of air into the turbulent flame. They were then compared with other experiments on the flow of hot gases. Some recent experiments on the effects of wind on such flames were also reported.

Albini (1979) presented a predictive model for calculating the maximum spot fire distance to be expected when firebrands are thrown into the air by the burning of tree crowns either individually or in small groups. Variables included in the model are the quantity and surface/volume ratio of foliage in the burning tree(s), the height of the tree(s), and the wind field that transports the firebrands, and the firebrand burning rate. Many aspects of the processes modeled were as that time incompletely understood and so are only weakly represented. Improved models were needed for all of the processes before predictions can be made with certainty, but a step-by-step, graphical procedure was presented here for test and evaluation in the field. No validation data were available in that time.

Chase (1981) presented equations for calculating maximum spot fire distance from firebrand sources in the Intermountain West based on prevailing windspeed, vegetation cover, and terrain in the area. The equations included the capability to predict spotting distance from a torching tree(s) or from a continuous flame source such as slash piles or jackpots of heavy fuels. The equations could be used on a programmable pocket calculator. Potential uses were seen in fire management planning and real-time fire behavior predictions.

Albini (1981) published a report which extends a predictive model tor estimating spot fire distance from burning trees. A formula was given for the maximum firebrand lotting height by continuous flames, such as from burning piles, jackpots of woody fuel, and so forth. This height may be used directly in the algorithm detailed in the earlier work. Also, formulas and graphs were given for estimating maximum spot fire distance when the terrain downwind of the source of firebrands is covered by vegetation of low height I bare ground, or water, rather than forest. This extension was implemented by establishing an “effective” or minimum vegetation height to be used in the formulas given in his earlier work. The effective vegetation cover height so derived depends on the firebrand initial height.

Albini (1983a) documented a speculative model of the process by which firebrand particles are lofted into the air through the action of buoyancy-induced airflow near the head of a wind-driven fire in surface fuels. It is postulated that the particles are lofted by strong thermals generated by the fire. The fire and the thermals it generates are idealized as being two-dimensional, for analytical tractability. It is further postulated that the fire generates the thermals because the intensity of the fire fluctuates with time in response to variations in windspeed or "gustiness." An increase in intensity above the average value, sustained for some period of time, is assumed to give birth to a line thermal with energy/length (or "strength") equal to the excess energy/length afforded by the intensity excursion. Albini previously published theoretical power spectral densities of intensity variations of line fires in typical wildland fuels, based on a model for the dynamic response of the fire to windspeed variations and an empirical power spectrum function for horizontal wind gustiness near the surface. A simple stochastic sequence of excursions of intensity is used as a surrogate process to approximate these power spectra and so allow explicit expression of thermal strength as a function of windspeed, mean fire intensity, and fuel type. The trajectories of particles lofted by line thermals have been described elsewhere by the author. Maximum viable firebrand height was shown to be proportional to the square root of the thermal strength, and the downwind drift distance during lofting proportional to the product of windspeed and the square root of the loft height. The equations for predicting maximum firebrand height and drift distance during lofting were summarized here in simple form for easy field use. Once the maximum viable firebrand height is known, it can be used to predict the distance downwind that the particle will travel before it returns to the ground. Equations for this calculation have been published elsewhere, and are available as pocket calculator programs. Because several elements of the model process are both speculative and not subject to direct validation, these results are to be considered tentative. Field tests of the spotting distance predictions are sought as a means of testing the utility of the model.

Albini (1983b) published a paper in which are introduced results of a research provided. The motion of a strong line thermal in an unstratified atmosphere was modeled to estimate a bound for its capability to lift firebrand particles. It was found that the maximum height of a viable firebrand is roughly proportional to the square root of thermal strength. The horizontal distance traveled from the point of origin to the point where free descent begins was calculated for two wind-speed profiles with height, assuming the transporting thermal to be embedded in the wind field. This downwind drift distance was shown to be both significant and sensitive to the windspeed profile. This model, with the results given here, permits the rapid estimation of maximum spot fire distances under field conditions.

Chase (1984) developed extensions of equations for pocket calculators to calculate the maximum spot fire distance to include wind-driven fires burning in surface fuels as a firebrand source. Predictions were based upon prevailing windspeed, vegetational cover, and local terrain. The equations could be used on a programmable pocket calculator. Previous methods of calculating spotting distance from torching trees and burning piles were also included.

Morton (1965) discussed questions involved in the formulation of fire plume theories. Therefore, few solutions were given in detail but no attempt was made to link the dynamical effects with those due to radiation. According to Morton, theoretical treatments for plumes of very hot gas in a uniform still environment and for turbulent diffusion flames may be based on an extension of the treatments for weakly buoyant plumes, provided that due allowance is made for the large variations in density and for the effects of radiation. He gave a discussion of the modifications needed for a theory of very hot plumes, and the dynamic and radiative effects are treated here separately. In strongly buoyant plumes, a modified entrainment function must be used, and variations of mass and inertia per unit volume with varying temperature must be taken into account. The full equations for strongly buoyant plumes may be transformed approximately into a set of equations already used to study weakly buoyant forced plumes, and this reduction shows that very hot plumes have a reduced rate of spread at first. In an opaque plume, where the flow is turbulent and the length scale of the energy-containing eddies is much larger than the mean free path for radiation, heat transfer by radiation can be separated into a vertical radiative diffusion and radiation from the plume boundaries to the distant environment. The vertical transfer is often much less than that from the boundaries and may be neglected except in the immediate neighborhood of the source. In cases of extreme cooling by radiation, longitudinal diffusion may no longer be neglected.

Morris (1987) described the nature of spotting from wind driven surface fires as it affects practical fire behavior modeling. He described how Albini's spotting model (Albini 1979, 1981, 1983) was simplified without adverse effect on accuracy. The simplified model has been implemented in the BEHAVE fire prediction and fuel modeling computer system.

Albini et al. (2012) presented a mathematical model for predicting the maximum potential spot fire distance from an active crown fire. This distance can be estimated from the height of the flame above the canopy top, wind speed at canopy-top height and final firebrand size (i.e. its residual size on alighting), represented by the diameter of a cylinder of woody char. The complete model system comprises several sub models or components: a model for the height and tilt angle of the wind-blown line-fire flame front, a simplified two-dimensional model of the wind-blown buoyant plume from the fire, an assumed logarithmic wind speed variation with height, and an empirically based model for the burning rate of a wooden cylinder in cross flow, which represents the firebrand. The trajectory of the burning particle is expressed analytically from where it leaves the lower boundary of the plume until it enters the canopy top. Adding the horizontal distance of this flight to that of the point where the particle can no longer be held aloft by the plume flow gives a spotting range that depends on the final diameter of the burning particle. Comparisons of model output with existing information on crown fire spotting distances has initially proved encouraging but further evaluation is warranted.

Butler et al. (2004) developed a numerical model for the prediction of the spread rate and intensity of forest crown fires. The model is the culmination of over 20 years of previously reported fire modeling research and experiments. This study presents a brief review of the development and structure of the model followed by a discussion of recent modifications made to formulate a fully predictive model. The model is based on the assumption that radiant energy transfer dominates energy exchange between the fire and unignited fuel with provisions for convective cooling of the fuels ahead of the fire front. Model predictions are compared against measured spread rates of selected experimental fires conducted during the International Crown Fire Modelling Experiment. Results of the comparison indicate that the closed form of the model accurately predicts the relative response of fire spread rate to fuel and environment variables but overpredicts the magnitude of fire spread rates.

Canadian Forest Fire Behavior Prediction (FBP) System provides quantitative estimates of potential head fire spread rate, fuel consumption, and fire intensity, as well as fire descriptions. With the aid of an elliptical fire growth model, the FBP system gives estimates of fire area, perimeter, perimeter growth rate, and fire behavior at the head, flanks, and back of a fire. *Rate of Spread* (ROS) is the predicted speed of the fire at the front or head of the fire (where the fire moves fastest) and takes into account both crowning and spotting. It is measured in meters per minute and is based on the Fuel Type, Initial Spread Index, Buildup Index, and several fuel-specific parameters such as phenological state (leafless or green) in deciduous trees, crown base height in coniferous trees, and percent curing in grasses. *Total Fuel Consumption* (TFC) is the predicted weight of fuel consumed by the fire both on the forest floor and in the crowns of the trees. It is measured in kilograms per square meter of ground surface and is based on Foliar Moisture Content, Surface Fuel Consumption, and Rate of Spread. *Head Fire Intensity* (HFI) is the predicted intensity, or energy output, of the fire at the front or head of the fire. It has become one of the standard gauges by which fire managers estimate the difficulty of controlling a fire and select appropriate suppression methods. It is measured in kilowatts per meter of fire front and is based on the Rate of Spread and the Total Fuel Consumption. *Crown Fraction Burned* (CFB) is the predicted fraction of the tree crowns consumed by the fire. It is based on Buildup Index, Foliar Moisture Content, Surface Fuel Consumption, and Rate of Spread. *Fire Type* (FT) provides a general description of the fire. It is based on the Crown Fraction Burned (CFB). If the CFB is less than 0.1 (10%), then the fire is a surface fire. If the CFB is 0.9 (90%) or more, the fire is a continuous crown fire. If the CFB is between 0.1 and 0.9, the fire is an intermittent crown fire.

Cruz et al. (2003) developed models to predict canopy base height (CBH), canopy fuel load (CFL) and canopy bulk density (CBD) through linear regression analysis and using common stand descriptors (e.g. stand density, basal area, stand height) as explanatory variables. The models developed were fuel type specific and coefficients of determination ranged from 0.90 to 0.95 for CFL, between 0.84 and 0.92 for CBD and from 0.64 to 0.88 for CBH. To estimate canopy fuel stratum characteristics of four broad fuel types found in the western United States and adjacent areas of Canada, namely Douglas-fir, ponderosa pine, mixed conifer, and lodgepole pine forest stands, data from the USDA Forest Service's Forest Inventory and Analysis (FIA) database were analyzed and linked with tree-level foliage dry weight equations. Although not formally evaluated, the models seem to give a reasonable characterization of the canopy fuel stratum for use in fire management applications.

Coen et al. (2013) described a wildland fire-behavior module (WRF-Fire), which was integrated into the Weather Research and Forecasting (WRF) public domain numerical weather prediction model. The fire module is a surface fire-behavior model that is two-way coupled with the atmospheric model. Near-surface winds from the atmospheric model are interpolated to a finer fire grid and are used, with fuel properties and local terrain gradients, to determine the fire’s spread rate and direction. Fuel consumption releases sensible and latent heat fluxes into the atmospheric model’s lowest layers, driving boundary layer circulations. The atmospheric model, configured in turbulence-resolving large-eddy-simulation mode, was used to explore the sensitivity of simulated fire characteristics such as perimeter shape, fire intensity, and spread rate to external factors known to influence fires, such as fuel characteristics and wind speed, and to explain how these external parameters affect the overall fire properties. Through the use of theoretical environmental vertical profiles, a suite of experiments using conditions typical of the daytime convective boundary layer was conducted in which these external parameters were varied around a control experiment. Results showed that simulated fires evolved into the expected bowed shape because of fire–atmosphere feedbacks that control airflow in and near fires. The coupled model reproduced expected differences in fire shapes and heading-region fire intensity among grass, shrub, and forest-litter fuel types; reproduced the expected narrow, rapid spread in higher wind speeds; and reproduced the moderate inhibition of fire spread in higher fuel moistures. The effects of fuel load were more complex: higher fuel loads increased the heat flux and fire-plume strength and thus the inferred fire effects but had limited impact on spread rate.

Bogdos and Manolakos (2013) described a fire behavior simulation workflow using FlogA. In order to understand the way FLogA handles a wildfire simulation, there are next described the input and output of the simulation engine, the Web services it utilizes, and how the simulation procedure is organized into a complete workflow. The forest area is considered as a grid of cells, with every cell exhibiting different topography and weather condition characteristics. The simulation accepts as input a set of raster ASCII files. “Static” simulation input consists of the forest’s topographic parameter layers, namely slope, aspect and fuel models, which are considered to be fixed for the duration of the fire event. “Dynamic” simulation input consists of current weather related parameter layers, namely wind speed and direction and fuel moisture content. In addition, simulation input must also include information about the starting point(s) of the fire event (ignition cells). Regarding the output, fireLib (Bevins, 1996) is used to determine the time of fire’s arrival to the neighboring cells using cellular automata-based fire propagation algorithms. Output information includes the fire’s time of arrival and the flame length for each cell of the forest’s grid. An advantage of the simulation engine output is the simplicity of its ASCII raster format that can be transformed into informative geo-animations. Using the Google Earth browser plugin these animations are projected over the actual forest map. The user can handle them effectively through the user interface, which translates user input into Google Earth API instructions. FLogA can generate automatically the BEHAVE fuel model raster file for any forest area defined in Europe by utilizing land cover classification data published by the Coordination of Information on the Environment (CORINE). In order to enable FLogA to do this, they have created a service using a set of publicly available shape files from CORINE's Web site covering the entire Europe. They transcoded the CORINE land cover classification codes into BEHAVE fuel model codes using a mapping method suggested by (Kalabokidis et al. 2004), so currently the mapping offers an adequate match for southern Europe. FLogA also uses a hotspot reporting service that is based on the MODIS Active Fire/Hotspot Data, a product of NASA's MODIS (Moderate Resolution Imaging Spectroradiometer) Rapid Response System (NASA/University of Maryland). Delivered information is near real-time with at least four daily MODIS observations for almost every area on the equator e due to overlapping satellite orbits the number of overpasses increases the closer an area is to the poles. Finally, FLogA utilizes the weather service of Wunderground Data Feed to obtain the wind speed, wind direction and relative air humidity, measured by the closest to the forest area Meteorological Aerodrome Report (METAR) station. The simulation procedure can be triggered manually, by introducing hypothetical hotspots, or automatically, via detected MODIS hotspots.

Linn, R. (1997) developed a transport model for prediction of wildfire behavior. The model is entirely physics-based and therefore self-determining (a self-determining propagation rate) rather than empirical. The transport approach allows one to represent a large number of environments including transition regions such as those with nonhomogeneous vegetation and terrain. Some of the most difficult features to treat are the imperfectly known boundary conditions and the fine scale structure that is unresolvable, such as the specific location of the fuel or the precise incoming winds. The author accounted for the microscopic details of a fire with macroscopic resolution by dividing quantities into mean and fluctuating parts similar to what is done in traditional turbulence modelling. He developed a complicated model that includes the transport of multiple gas species, such as oxygen and volatile hydrocarbons, and tracks the depletion of various fuels and other stationary solids and liquids. From this model he also formed a simplified local burning model with which he performs a number of simulations for the purpose of demonstrating the properties of a self-determining transport-based wildfire model.

Computational Fluid Dynamics (CFD) models are powerful research tools for studying fire dynamics. However, their application to wildland fire scenarios requires evaluation against relevant experimental data. To progress the current understanding of the fidelity of a CFD approach to simulating wildland fire dynamics, a dataset from an experimental fire was used by Mueller et al. (2021, as a test case. First, implications of the level of detail provided to the model, in the form of fuel structure and wind, were evaluated. Second, the predictions of both fire behavior (e.g. spread rate) and the driving combustion processes (e.g. heat flux) were compared to the experiment. It was found that both increasing the detail in canopy fuel structure and implementing turbulent boundary conditions had a minor impact. It was further found that the model reproduced fire behavior in the mid-range of experimental observations and that the representation of local combustion processes was qualitatively consistent. This work demonstrated the promising capabilities of the modeling approach used here, while showing that some of its aspects require further investigation and possibly more development.

Vasconcelos, Guertin (1992) in their paper described the concepts behind FIREMAP and compares simulation results with a real fire occurrence. The predicted burned area (138 ha) and the real burned area (132 ha) had a similar overall shape. FIREMAP is a simulation system designed to estimate wildfire characteristics in spatially non-uniform environments and simulate the growth of fire in discrete time steps. This simulation system integrates Rothermel's behavior prediction model (Rothermel 1972) with a raster-based geographic information system. The outputs can be displayed as digital maps.

Scott and Reinhardt (2001) developed quantitative methods for assessing crown fire hazard. Links among existing mathematical models of fire behavior were used to develop two indices of crown fire hazard—the Torching Index and Crowning Index. These indices can be used to ordinate different forest stands by their relative susceptibility to crown fire and to compare the effectiveness of crown fire mitigation treatments. The coupled model was used to simulate the wide range of fire behavior possible in a forest stand, from a low-intensity surface fire to a high-intensity active crown fire, for the purpose of comparing potential fire behavior. The hazard indices and behavior simulations incorporate the effects of surface fuel characteristics, dead and live fuel moistures (surface and crown), slope steepness, canopy base height, canopy bulk density, and wind reduction by the canopy. Example simulations were provided for western Montana Pinus ponderosa and Pinus contorta stands. Although some of the models presented here have had limited testing or restricted geographic applicability, the concepts will apply to models for other regions and new models with greater geographic applicability.

2.3.2.3 Assessment of relevant models

A summary assessment of selected fire behavior models is provided in appendix 5.3 (Table 47).

The use of CFD models for studying wildland fires, which can span a large range of scales and involve complex conditions (porous fuels, weather effects, etc.), continues to draw more significant debate within the research community (Alexander et al. 2013). Therefore, evaluating such models against data from field-scale fires is an important step in understanding the current capabilities of the approach, while also helping to identify mechanistic shortcomings which require additional model development (Alexander et al. 2013, Mueller et al. 2017, Mueller et al. 2018). Some previous studies have compared detailed physics-based fire behavior models to measurements from field-scale experimental fires in grasslands (e.g., Mell et al. 2009, Morvan et al. 2018), and forested environments (Skowronski et al. 2011, Lin et al. 2009). However, these have been based on a limited number of experiments (essentially two campaigns in grasslands, and one in a forest). While these studies are valuable for cross-model comparisons, more are needed at this scale, encompassing a range of fuel and environmental conditions. Moreover, spread rate is typically the main, or only, direct point of comparison, and only the studies of Dupuy et al. (2014) and Pimont et al. (2014) have investigated model predictions of quantities such as temperature, velocity, and heat flux at field-scale. Such quantities can shed light on whether seemingly accurate predictions of fire behavior are indeed a function of adequate representations of the driving combustion processes.

2.3.3 Relevant tools

2.3.3.1 Overview of relevant tools

Table 4 provides an overview of tools related to fire behavior analysis.

Table 4: Overview of tools used for fire behavior analysis.

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
T21.1	Wildfire Analyst	SW-GIS style: desktop version (windows and mac). Seamless compatibility with ESRI ArcGIS	A, B	Provides real-time wildfire behavior modelling, wildfire spread; risk analysis, GIS. Outputs in form of maps, charts, reports.	Unspecified
T21.2	WFA Pocket	SW-GIS style: desktop version (windows and mac). Seamless compatibility with ESRI ArcGIS. Android, iOS, Windows 64x, Mac OS, Linux.	A, B	Provides real-time wildfire behaviour modelling, wildfire spread; risk analysis, GIS. Outputs in form	Unspecified

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
				of maps, charts, reports.	
T21.3	BehavePlus (ver 6)	S/W: PC - based. Windows platform (10, 7, Vista, 2000)	A	Can predict rate of spread, fire intensity, flame lengths and other characteristics of fire behaviour.	Rothermel surface fire spread model; 13 fuel model inputs for USA (Rothermel 1972, Albini 1976, Anderson 1982) with updates.
T21.4	Nexus 2.1	S/W-PC based: Windows	A, B	Can predict rate of spread, fire intensity, flame lengths and other characteristics of crown and surface fire behaviour.	Rothermel's (1972) and Rothermel's (1991). Van Wagner (1977).
T21.5	FlamMap 6.0	S/W-PC based: Windows 64-bit	A, B	Can predict rate of spread, fire intensity, flame lengths and other characteristics of fire behaviour.	includes FARSITE (Finney 1998, 2004) and FlamMap BASIC (Finney 2006), Minimum Travel Time (MTT, Finney 2002, 2006), Treatment Optimization Model (Finney 2001, 2006, 2007), and Conditional Burn Probability (Finney 2005, 2006). It incorporates the following fire behavior models: Rothermel's (1972) surface fire spread model, Van Wagner's (1977) crown fire initiation model, Rothermel's (1991) crown fire spread model, Albini's (1979) spotting model, Finney's (1998) or Scott and Reinhardt's (2001)

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
					crown fire calculation method, and Nelson's (2000) dead fuel moisture model. This allows conditioning of dead fuels in each pixel based on slope, shading, elevation, aspect, and weather.
T21.6	FARSITE 4.0	S/W: included in FlamMap		Can predict rate of spread, fire intensity, flame lengths and other characteristics of crown and surface fire behaviour.	includes FARSITE (Finney 1998, 2004) and FlamMap BASIC (Finney 2006), Minimum Travel Time (MTT, Finney 2002, 2006), Treatment Optimization Model (Finney 2001, 2006, 2007), and Conditional Burn Probability (Finney 2005, 2006). It incorporates the following fire behavior models: Rothermel's (1972) surface fire spread model, Van Wagner's (1977) crown fire initiation model, Rothermel's (1991) crown fire spread model, Albini's (1979) spotting model, Finney’s (1998) or Scott and Reinhardt’s (2001) crown fire calculation method, and Nelson's (2000) dead fuel moisture model. This allows conditioning of dead fuels in each pixel based on slope, shading, elevation,

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
					aspect, and weather.
T21.7	CFIS (Crown Fire Initiation and Spread)	S/W: PC based: Windows (*.exe) and *.xls.	A, B	Provides crown fires modelling and simulation. The main outputs of CFIS are: a) the likelihood of crown fire initiation or occurrence; b) the type of crown fire (active vs. passive) and its rate of spread; and c) the minimum spotting distance required to increase a fire's overall forward rate of spread.	Cruz et al., (2003)
T21.8	PyTorch	Python	A, B	Provides fire spread detection using aerial or satellite images using machine learning.	Transfer Learning
T21.9	WRF-Fire	Cloud-based, open source	A, B	Provides fire spread modelling based on real-time weather situation.	Coen et al. (2013); Mandel et al. (2007); Mandel et al. (2011)
T21.10	FLogA	Web application	A, B	Provides wildfire simulation. Simulates and animates the behavior of the evolving fireline under different weather conditions.	Rothermel (1972); Anderson (1982); fireLib

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
T21.11	Prometheus	S/W: 64-bit Windows 10 or Windows Server 2008 R2	A, B	Forecasts wildland fire growth for operational decision support. Assesses the effectiveness of alternative fuel management strategies. Allows planning prescribed burns. Provides forensic support for wildfire investigations. Allows studying the role of fire in establishing and maintaining landscape patterns. Provides spatial and temporal estimates of smoke emissions.	Fire growth simulation model based on the Fire Weather Index (FWI) and Fire Behaviour Prediction (FBP) sub-systems of the Canadian Forest Fire Danger Rating System (CFFDRS).
T21.12	Burn P3	S/W: 64-bit Windows 10 or Windows Server 2008 R2	A, B	Computes burn probabilities for large landscapes; Produces additional outputs, such as fire intensity map; Extracts fire statistics and simulated fire perimeters.	Uses the Prometheus fire-growth engine.
T21.13	FireFamily+ (FF+)	Windows	A, B	Based on the US National Fire Danger Rating System (NFDRS) using hourly or daily fire weather observations primarily from Remote Automated Weather Stations (RAWS)	Unspecified

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
				provides information on fuel moisture and Fire Danger.	
T21.14	FIREMON	Windows	A, C	Plot level sampling system designed to characterize changes in ecosystem (fire effects) attributes over time.	USDA
T21.15	FOFEM	Windows	A, B, C	Provides fire effects model, tree mortality model, fuel consumption model, smoke production model and soil heating model.	USDA
T21.16	FEIS	ArcGIS related (Windows basically)	A, C	Provides information, data on species reviews, fire regime and fire studies.	USDA
T21.17	ArcFuels	Web-based	A, B, C	Provides potential fire behavior metrics, including fire spread, intensity, likelihood, and ecological risk which need to be analyzed for proposed treatment alternatives.	USDA
T21.18	WFAS	Windows, Linux and OSX	A, B	An integrated, web-based resource to support fire management decisions. The system provides	CFD model

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
				multi-temporal and multi-spatial views of fire weather and fire potential, including fuel moistures and fire danger classes from the US National Fire Danger Rating System (NFDRS), Keetch-Byram and Palmer drought indices, lower atmospheric stability and satellite-derived vegetation conditions. It also provides fire potential forecasts from 24 hours to 30 days.	
T21.19	WFDS	Windows	A, B	Provides modelling of spread of fire on flat surface, burning of a single tree based on CFD model application.	CFD model. Relevant to WUI dynamics.
T21.20	PHOENIX Rapidfire	Windows	A, B	Predicts the potential progression of fire (fire spread, flame height, fire intensity, fire size) across virtual landscapes under different weather and fire suppression scenarios.	Fire characterization model (see detailed description)
T21.21	Aurora	Windows	A, B	Calculates Fire Behaviour Index, Rate of Spread	Cruz et al. (2015)

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
				and other behaviour variables using published models for Australian vegetation, aligns with Australian Fire Danger Rating System.	
T21.22	HIGRAD/FIRETEC	Windows, Linux	A, B	Physics-based, 3-D computer code designed to simulate the constantly changing, interactive relationship between crown or surface fire and its environment.	Linn (1997)
T21.23	FireStation	Windows basically	A, B	Provides numerical simulation of fire spread on complex topography.	Lopes et al. (2002)
T21.24	FIREMAP	Windows, Linux, QGIS based	A, B	Estimates wildfire characteristics in spatially non-uniform environments and simulate the growth of fire in discrete time steps.	Rothermel (1972)
T21.25	QGIS Fire Mapping Tool	Windows	B	Processes the Landsat imagery, generates fire perimeters, and performs thresholding of the Landsat imagery to produce burn severity images.	Unknown

Tool Code	Tool Name or Title	Installability	Tool Applicability in Phases	Capabilities / Restrictions of the Model	Integrated Model
T21.26	Fsim	Windows	A	Simulates the growth and behavior of hundreds of thousands of fire events for risk analysis across large land areas using geospatial data on historical fire occurrence, weather, terrain, and fuel conditions. Effects of large fire suppression on fire duration and size are also simulated.	Unspecified
T21.27	WFDSS	Windows	A, B	Real-time incident decision making and documentation and providing a spectrum of risk-based functionality, including operational risk assessment, probabilistic fire spread modelling and exposure assessment.	Unspecified
T21.28	FROST Family	ArcGIS related (Windows basically)	A, B, C	A risk-based fire regime simulator for assessing the impacts of fire and land management on human and environmental values across landscapes.	Unspecified

2.3.3.2 Description of relevant tools

Wildfire Analyst (WFA)

Wildfire Analyst™ is a cloud-based SaaS offering that provides on-demand wildfire spread prediction capabilities to support operational response, what-if scenario analysis, and wildfire risk forecasting. The integration with advanced weather prediction data affords the development of hourly risk forecasts up to five days in advance. Millions of wildfire spread simulations are conducted daily to derive accurate risk metrics reflecting where fires will spread and the possible impacts from those fires. The spread simulations derive potential impacts providing the baseline for consequence analysis and operational decision making. (TECHNOSYLVA 2023a). When wildfires occur, it is important to quickly understand where the fire is going and what it will impact. FireSim™ provides an on-demand capability within WFA-E to create a spread prediction and obtain detailed information on potential impacts within seconds of incident notification. Impact analysis, including at-risk populations, structures and buildings, critical facilities, and company assets, is automatically undertaken with each prediction – all within 30 seconds. This information is critical for infrastructure protection, response, and resource prioritization. FireSim™ includes several advanced prediction models to identify where a fire will spread, and what areas are vulnerable. Probabilistic models allow the user to incorporate a measure of uncertainty by varying key inputs for simulations, often providing a better comfort level during complex incidents. Users can switch between different simulation modes and generate new simulations within seconds, with a suite of tools to review and compare outputs. Each simulation assesses the likelihood of the fire escaping initial attack based on the spread, growth and suppression difficulty characteristics. This metric aids decision makers in determining which fire is more of a concern and where resources may be prioritized based on the spread and damage potential. Potential impacts of a fire are automatically calculated for each simulation using detailed data for population, buildings and critical facilities – all within 30 seconds. FireSim uses a comprehensive integrated database that affords consequence analysis and tools to review and query potential impacts. Advanced urban encroachment algorithms are employed to ensure that an accurate analysis of WUI and urban fringe impacts are captured. This is a key element of accurately assessing potential impacts for a fire. The advanced encroachment algorithms are based on the analysis and calibration with actual damage assessment data compiled over the past 13 years. Through the integration with real-time detection data, FireSim is able to calibrate simulations on-the-fly to incorporate observed field observations. The solution has unique integration with high resolution detection sources to facilitate this analysis. Machine Learning models are employed to analyze and integrate this detailed observation data into model prediction. Detailed reports documenting the input weather and landscape conditions, ground and canopy fuels, fuel moisture and fire behavior outputs are automatically created for each simulation. This includes a summary one-pager and a detailed multi-page report. The reports are ideal for sharing prediction data externally with others while not requiring access to FireSim. (TECHNOSYLVA 2023b)

WFA Pocket

The Wildfire Analyst™ Pocket Edition application provides the wildland fire community with operational fire behavior tools for use in the field. It is a mobile app that embodies the latest wildland fire behavior science into a robust tool for the firefighter and Fire Behavior Analyst. Leveraging the science developed by the US Forest Service Missoula Fire Sciences Lab, this app enhances calculations with a 3D interactive map interface, real-time weather integration, and seamless fuels data assimilation.

The app works either connected or disconnected, providing outputs and results in a form that is readily understood and usable. WFA Pocket uses concepts and formulas developed by the US Forest Service Missoula Fire Sciences Lab to perform fire behavior calculations. It is a culmination of the wonderful science made possible by the work of applied wildfire scientists and wildland firefighters across the world. WFA Pocket compiles knowledge gained from the five plus decades of applied research on wildfire behavior, and is intended to serve as a companion to the Fire Behavior Field Reference Guide (PMS 437). WFA Pocket has been developed to work across multiple devices, both mobile and desktop. Real time integration to weather services and LANDFIRE fuels data allows users to define and modify inputs to best match observed conditions in-the-field. The app includes significant enhancements to the traditional calculators by providing 3D interactive mapping, real-time weather data integration, and fuels data assimilation. WFA

Pocket is available for Android, iOS, Windows, Mac and Linux operating systems. Android and iOS versions are available through the Google Play and Apple App stores. (WFA POCKET 2023)

BehavePlus (ver 6)

BehavePlus is among the most widely used fire management systems in the US, with a significant use outside of the US as well (Andrews 2010). The BehavePlus fire modeling system is a Windows®-based computer program that can be used for any fire management application that needs to calculate fire behavior. It uses specified fuel and moisture conditions to simulate surface and crown fire rate of fire spread and intensity, probability of ignition, fire size, spotting distance, and tree mortality. It is designed for use in a range of tasks including wildfire behavior prediction, prescribed fire planning, fire investigation, fuel hazard assessment, fire model understanding, communication and research. BehavePlus is based on mathematical models for fire behavior, fire effects and fire environment. It is a point system for which conditions are constant for each calculation, but is designed to encourage examination of the effect of a range of conditions through tables and graphs. BehavePlus is successor to BEHAVE, which was developed in 1977 and became available for field application in 1984. It was updated to BehavePlus in 2002. Updates through version 5 have added features and modelling capabilities. It is organized according to calculation modules (IGNITE – probability of ignition, SURFACE – surface fire behaviour, CROWN – crown fire behavior, SAFETY – safety zone size, SIZE – point source fire size and shape, CONTAIN – fire containment due to suppression action, SPOT – maximum spotting distance, SCORCH – crown scorch height), MORTALITY – probability of tree mortality). Modules can be used independently or linked together with results from one being used as input to another. BehavePlus includes over 40 fire models, described in 58 reference papers (Andrews 2014). The 53 standard fire behaviour fuel models and custom fuel models are counted as one 'model'. BehavePlus or BEHAVE has sometimes incorrectly been used as a synonym for the Rothermel surface fire spread model, which is only one of many models in the system.

The core of the SURFACE module is the Rothermel (1972) surface fire spread model, with some minor adjustments (Albini 1976a), which calculates head fire rate of spread in surface fuels. The model describes fires advancing steadily, independent of the source of ignition (quasi steady-state). Fire behavior in the flaming front is primarily influenced by fine fuels. The fuel bed is assumed to be horizontally uniform and continuous, within ~1.8 m of the ground. Fireline intensity and flame length are based on models developed by Byram (1959), using Albini's (1976b) method for using those models with the Rothermel model. The fuel consumed in the active flaming front is based on flame residence time (Anderson 1969) calculated from the characteristic surface-area-to-volume ratio of the Rothermel model. The relationship among rate of spread, heat per unit area, fire line intensity and flame length is displayed in the fire characteristics chart (Andrews and Rothermel 1982). A simple chart is available in BehavePlus; a supplemental program gives more options (Andrews et al. 2011). Calculation of surface fire spread rate and intensity requires a description of the surface fuel, midflame wind speed, slope and fuel moisture.

The CROWN module in BehavePlus includes models for spread rate and intensity (Byram 1959; Thomas 1963; Rothermel 1991), transition from surface to crown fire (Van Wagner 1977, 1989, 1993; Finney 1998; Scott and Reinhardt 2001), conditions for active crown fire (Van Wagner 1977) and fire type (Van Wagner 1993; Finney 1998; Scott and Reinhardt 2001). The models were developed independently and, although not specifically designed to work together, the CROWN module provides a means of modelling the range of fire behavior (Finney 1998; Scott and Reinhardt 2001). Many important factors that affect crown fire are not included (Werth et al. 2011). It is especially important for a user to be aware of model limitations in predicting extreme fire behavior (Cruz and Alexander 2010). The model for crown fire rate of spread is a simple correlation based on seven crown fires (Rothermel 1991). The inputs are only 20-ft wind speed and surface fuel moisture. The model does not utilize a description of either the surface or the crown fuels. It was designed to predict an average crown fire spread rate over several hours. Due to the nature of the model, spotting is included as a mechanism of spread. BehavePlus does not include a reduction to spread rate based on crown fraction burned as does FARSITE, which includes spotting as a separate influence in fire growth modelling (Van Wagner 1993, Finney 1998, Scott and Reinhardt 2001).

The moisture content of surface fuels is used to calculate spread rate and intensity in the SURFACE and CROWN modules; and foliar moisture, representing the moisture of live conifer needles, is used to calculate transition to crown fire in the CROWN module (see the crown fire section below). In addition, there is a fine dead fuel moisture tool that is not directly linked to any of the calculation modules.

The SPOT module includes models for maximum spotting distance from torching trees (Albini 1979; Chase 1981), burning piles (Albini 1981) and wind-driven surface fires (Albini 1983a, 1983b; Chase 1984; Morris 1987). In each case, the lofting height of potential firebrands is found from the flame structure. The ambient wind then carries the firebrand, which is assumed to be a wood cylinder. Model predictions are for maximum spotting distance based on the assumption that firebrands are sufficiently small to be carried some distance, yet large enough to start a fire when they reach the ground.

The IGNITE module includes models for probability of ignition from a firebrand (Schroeder 1969) and from lightning (Latham and Schlieter 1989). The model for probability of ignition from a firebrand is based on an experiment in which matches were dropped on pine needles. The calculation uses fine dead fuel moisture, air temperature and fuel shading from the sun. The model for probability of ignition from cloud-to-ground lightning flashes is based on laboratory experiments using different fuel types (litter, duff, etc.). Other inputs include depth of the litter and duff layer, fuel moisture and lightning discharge type (negative, positive or unknown).

The SAFETY module is based on a model for minimum separation distance between the fire and a person as a function of flame height (Butler and Cohen 1996, 1998a, 1998b). The model is based on radiant heating only. Convective energy transport in the form of gusts, fire whirls or turbulence is not included. A safety zone is an area to which firefighters can retreat and not have to deploy fire shelters to remain safe. The size of a safety zone also considers the number of people and equipment to be protected.

The SCORCH module includes a model for the height above the ground that the temperature in a convection column reaches lethal temperature (60°C) to kill live crown foliage (Van Wagner 1973). The relationship between fire behavior and crown scorch height was derived from measurements on 13 outdoor experimental fires. Calculations are based on fire line intensity and also include the influence of air temperature and of wind on flame tilt.

The MORTALITY module includes models for probability of mortality, the likelihood that a tree will be destroyed by a fire as a result of crown scorch and cambium damage from surface fire flames. There is no consideration of root damage due to ground fire. The models are statistical, based on field data. The mortality equations (listed in the BehavePlus help system) variously include bark thickness, tree crown length scorched and tree crown volume scorched (Ryan and Reinhardt 1988; Ryan and Amman 1994; Reinhardt and Crookston 2003; Hood et al. 2007). BehavePlus includes the pre-fire, but not the post-fire, mortality models that are in FOFEM (Reinhardt 2003; Lutes 2012).

The SIZE module is used to calculate the size and shape of a fire burning from a point source ignition based on elliptical shape, with length-to-width ratio a function of effective midflame wind speed. The ignition point is the focus of the ellipse. Backing spread distance, maximum width of the fire and perimeter are determined by the ellipse equations. The user can specify effective wind speed and forward rate of spread, or those values can come from the SURFACE module.

The model for fire containment in the CONTAIN module estimates fire suppression resources necessary for containment of a fire growing from a point source. Multiple resources with various arrival times can be defined. The fire spread rate, shape and size at attack can either be user input or calculated by the SURFACE and SIZE modules. The shape of the free-burning point source fire is assumed to be that of an ellipse, with rate of spread constant over the time that line construction occurs. The rate of line construction is constant and work takes place simultaneously on both sides of the fire at an equal pace. Therefore, the specified line construction rate is split into two equal parts starting at the point of attack, either at the head or the rear. Suppression forces are assumed to be 100% effective; the fire will never breach the control line.

NEXUS is a system that includes fire behavior models for surface, crown, and transitional fires. Like the BEHAVE Fire Behavior Prediction and Fuel Modeling System (Andrews 1986) and the FARSITE Fire Area Simulator (Finney 1998), NEXUS predicts surface fire behavior using Rothermel's (1972) mathematical model. In addition, NEXUS estimates potential behavior of an active crown fire using Rothermel's (1991) correlation of crown fire spread rate with predictions based on his surface fire model. Based on Van Wagner (1977), NEXUS links these surface and crown fire predictions by estimating the transition points between surface fire, passive crown fire (also called torching, candling, and intermittent crowning), and active crown fire (also called a running or continuous crown fire). NEXUS estimates final (overall) fire behavior by scaling between surface and crown fire behavior predictions using a transition function. NEXUS also includes several sub models to compute secondary fire behavior outputs, such as fire size and shape. Because NEXUS estimates both NEXUS is the only tool surface and crown fire behavior, that wildland fire managers can use the user must provide inputs for surface and crown fire models to explore the links among existing both surface and crown fuels. The basic inputs for surface fire behavior prediction are the same as for BEHAVE. (Scott 1999)

NEXUS 2.1 is crown fire hazard assessment software that links separate models of surface and crown fire behavior to calculate indices of relative crown fire potential. Use NEXUS to compare crown fire potential for different forest stands, and to compare the effects of alternative fuel treatments on crown fire potential. NEXUS includes several visual tools useful in understanding how the operational surface and crown fire models used in the United States interact. Crown fire hazard assessment and behavior prediction is an emerging science. In NEXUS there are linked existing models of surface and crown fire behavior to produce a system to assess the potential for crown fires at the stand level. In 1998 the modeling system was initially implemented in a Microsoft Excel spreadsheet. At the time the authors envisioned a short life-span for NEXUS as other more established programs incorporated similar modeling capabilities. In 2001 they updated the spreadsheet and produced an online user's guide, but still did not envision a long life. In 2003, after obtaining funding, they re-coded NEXUS as a stand-alone computer program, finally shedding the Excel spreadsheet interface. In 2014 the National Park Service funded the update of Nexus to version 2.1, enabling the software to work on computers running Windows 7 and 8 operating systems. Because NEXUS 2.1 is licensed free of charge, there is no warranty for the program, to the extent permitted by applicable law. Except when otherwise stated in writing, the copyright holders and/or other parties provide the program "as is" without warranty of any kind, either expressed or implied, including, but not limited to, the implied warranties of merchantability and fitness for a particular purpose. (PYROLOGIX 2023)

FlamMap 6.0

FlamMap is one of the most widely accepted fire behavior modeling, fuel management and mapping software at landscape level (Finney, 2006). It is able to make fire behavior calculations for each location independently from one another with one set of environmental conditions (Finney 2006). FlamMap outputs provide useful information on fire management, well suited to landscape comparisons for determining dangerous fuel, topographic and weather combinations to assess fire hazard and prioritize the field crew in operative phases (Stratton 2004; Stratton, 2006; Ager, Finney 2009) and can be used by other fire management planning software without converting to another data format (Ager et al. 2011).

FlamMap is a fire analysis desktop application that runs in a 64-bit Windows Operating System environment. It can simulate potential fire behavior characteristics (spread rate, flame length, fireline intensity, etc.), fire growth and spread and conditional burn probabilities under constant environmental conditions (weather and fuel moisture). With the inclusion of FARSITE it can now compute wildfire growth and behavior for longer time periods under heterogeneous conditions of terrain, fuels, fuel moistures and weather. The FlamMap fire mapping and analysis system (Finney 2006) describes potential fire behavior for constant environmental conditions (weather and fuel moisture). Fire behavior is calculated for each pixel within the landscape file independently. Potential fire behavior calculations include surface fire spread, flame length, crown fire activity type, crown fire initiation, and crown fire spread. Dead fuel moisture and conditioning of dead fuels in each pixel based on slope, shading, elevation, aspect, and weather. With the inclusion of FARSITE, FlamMap can now compute wildfire growth and behavior with detailed sequences of weather conditions. The FlamMap fire mapping and analysis system includes FARSITE (Finney 1998, 2004) and FlamMap BASIC (Finney 2006), Minimum Travel Time (MTT, Finney 2002, 2006), Treatment Optimization Model (Finney 2001, 2006, 2007), and Conditional Burn Probability (Finney 2005, 2006). It incorporates the following fire behavior models: Rothermel's (1972) surface fire spread model, Van Wagner's (1977) crown fire initiation model, Rothermel's (1991) crown fire spread model, Albini's (1979) spotting model, Finney's (1998) or Scott and Reinhardt's (2001) crown fire calculation method, and Nelson's (2000) dead fuel moisture model. This allows conditioning of dead fuels in each pixel based on slope, shading, elevation, aspect, and weather. Because environmental conditions remain constant when using FlamMap, MTT, Burn Probability, and TOM it will not simulate temporal variations in fire behavior caused by weather and diurnal fluctuations as FARSITE does. Nor will it display spatial variations caused by backing or flanking fire behavior. These limitations need to be considered when viewing FlamMap output using these models in an absolute rather than relative sense. However, these outputs are well-suited for landscape level comparisons of fuel treatment effectiveness because fuel is the only variable that changes. Outputs and comparisons can be used to identify combinations of hazardous fuel and topography, aiding in prioritizing fuel treatments. The FlamMap software creates a variety of vector and raster maps of potential fire behavior characteristics (for example, spread rate, flame length, crown fire activity) and environmental conditions (dead fuel moistures, mid-flame wind speeds, and solar irradiance) over an entire landscape or for specific modeling applications these same outputs are limited to the simulation footprint (MTT and FARSITE). These raster maps can be viewed in FlamMap or exported for use in a GIS, or image format. The FlamMap software also creates a variety of vector outputs specific to each modeling system within the application. Gridded wind vectors are produced whenever WindNinja is used within the application and information on spotting (tabular and shapefile format) are also created. MTT creates MTT flow paths and MTT Arrival Contours. Within FARSITE, Wind and Spread Vectors, and FARSITE Perimeters are also produced. The FlamMap program requires eight geospatial data layers to create a valid landscape file (.LCP): Topographic (Elevation, Slope, Aspect), Fire Behavior Fuel Models, Forest Canopy Cover, Forest Canopy Height, Forest Canopy Base Height, Forest Canopy Bulk Density. FlamMap also requires information on dead and live fuel moistures, weather information, and wind speed and direction. WindNinja has been incorporated into FlamMap allowing for the use gridded wind information generated within the program for any simulation. Gridded winds using WindNinja's full mass and momentum solver can also be used in any simulation as well. Please see the WindNinja page for more information. (Missoula Fire Sciences Laboratory 2023)

A variety of options are available to display and export Farsite Visible Perimeters: (A) All Perimeters (will display and export every perimeter based on the Farsite Timestep value in the Farsite Model settings tab); (B) By Farsite Timestep Multiple (allows for displaying perimeters based on some multiple of the total available Farsite timesteps. The default value is 1 which is the equivalent of All Perimeters. The user can define this on multiples of the available timesteps, such as 6, 12, 24. Exceeding the total number of available timesteps will show only the last and final perimeter for the simulation is set at multiples of 6); (c) By Burn Period (will display the perimeters at the end of each specified Burn Period as set in the Burn Periods in the Model Settings tab shows two Burn Periods); (D) Final Perimeter Only (will display only the last perimeter from the last specified Burn Period shows only the last and final perimeter). FlamMap can use either random ignitions or a user supplied ignition file to determine burn probabilities across a given landscape under a constant set of fuels, wind and weather conditions. FlamMap can incorporate barriers into MTT analyses. Barriers can either be filled or unfilled. (Missoula Fire Sciences Laboratory 2023)

FARSITE 4.0

FARSITE is a computer program designed to simulate fire growth using existing models of fire behavior found in BEHAVE (Andrews 1986) and in the Canadian Forest Fire Behaviour Prediction System (Forestry Canada Fire Danger Group 1992). There are numerous uses for fire growth simulation, including planning for potential wildland fires, prioritizing and locating fuel treatments, tactical support on active fires, and fire incident reconstruction. Because FARSITE can generate spatial maps of fire behavior, it is useful for producing detailed analyses of fire behavior and fire effects on geographic information systems (GIS). This modeling capability however, requires digital maps of terrain and fuels in GIS formats, which is the main limitation for users wanting to do simulations. Nevertheless, FARSITE is widely used by State, Private, and Federal agencies in the U.S. who recognize the value of having GIS-based data on fuels and vegetation for a variety of applications. (Finney, Andrews 1998)

FARSITE incorporates existing models of surface fire, crown fire, point-source fire acceleration, spotting, and fuel moisture. This documentation of how the simulation was constructed, and how the individual fire behavior models perform, will be useful to researchers and managers who use FARSITE or are interested in fire growth simulation. (Finney 1998)

The models were integrated using a vector propagation technique for fire perimeter expansion that controls for both space and time resolution of fire growth over the landscape. The model produces vector fire perimeters (polygons) at specified time intervals. The vertices of these polygons contain information on the fire’s spread rate and intensity, which are interpolated to produce raster maps of fire behavior. Because fire behavior at each vertex is assumed independent of the others, the simulation outputs illustrate the strict spatial consequences to fire behavior of incorporating the models into a two-dimensional simulation. Simplified test conditions show that surface fire growth and intensity conform to idealized patterns. Similarities also exist between simulated crown fires and observed patterns of extreme wind-driven fires. Complex patterns of fire growth and behavior result from the spatial and temporal dependencies in the model.

The surface fire spread model used in FARSITE was the Rothermel spread equation (Albini 1976; Rothermel 1972). It computes the steady-state fire spread rate (m/min in a plane parallel with the ground surface at every vertex. The crown fire model used in FARSITE was developed by Van Wagner (1977, 1993) and is similar to its implementation in the Canadian Forest Fire Behavior Prediction System. It determines if the fire remains burning in the surface fuels or makes a transition to burning in crown fuels, and whether it spreads actively through the tree crowns or simply torches individual trees. The model assumes that the threshold for transition to crown fire is dependent on the crown foliar moisture content (percent on dry weight basis: determines crown ignition energy) and the height to crown base (Van Wagner 1989).

FARSITE automatically computes wildfire growth and behavior for long time periods under heterogeneous conditions of terrain, fuels, and weather. It is a deterministic modeling system, meaning that simulation results can be directly compared to inputs. This system can be used to simulate air and ground suppression actions as well as for fire "gaming," asking multiple "what-if" questions and comparing the results. FARSITE produces outputs that are compatible with Windows® and Workstation (e.g., Linux) graphics and GIS (Geographic Information System) software for later analysis and display. Results can be easily combined to create animated GIF (Graphics Interchange Format) images of projected fire growth as demonstrated below. Additionally, outputs can be created in spatial, linear and tabular formats. (Fire.org)

The latest version of FARSITE is version 4.0 which is multi-threaded. This means that the FARSITE program can be divided into pieces that run separately. Multi-threading is used to separate the fire growth simulation from the interface and to allow the fire growth calculations in FARSITE to make use of more than one processor. It integrates improved dead fuel moisture model which does all its calculations at the beginning of a simulation. Once this is done the rest of the simulation goes much faster. The fuel moistures even can be saved in a file to let future simulations skip the fuel moisture calculations. (Fire.org)

CFIS (Crown Fire Initiation and Spread)

According to Alexander et al. (2006), CFIS is a software tool or system incorporating several recently developed models designed to simulate crown fire behavior. The main outputs of CFIS are: (1)the likelihood of crown fire initiation or occurrence; (2) the type of crown fire (active vs. passive) and its rate of spread; and (3) the minimum spotting distance required to increase a fire’s overall forward rate of spread. The onset of crowning can be predicted through two distinct approaches. One approach relies on the knowledge of canopy base height and certain components of the Canadian Forest Fire Weather Index System and/or the 10-m open wind speed.The other approach requires the 10-m open wind, the estimated fine fuel moisture, fuel strata gap (or canopy base height), and an estimate of surface fuel consumption as inputs. Required inputs to predict crown fire rate of spread are 10-m open wind speed, estimated fine fuel moisture, and canopy bulk density. The minimum spotting distance to affect overall crown fire rate of spread, which assumes a point ignition and subsequent fire acceleration to an equilibrium rate of spread, requires the predicted crown fire spread rate and an ignition delay as inputs. The primary models incorporated into CFIS have been evaluated against experimental and wildfire observations with good results. CFIS has applicability as a decision support aid in a wide variety of fire management activities ranging from near-real time prediction of fire behavior to analyzing the impacts of fuel treatments on potential crown fire behavior. The core models underlying the CFIS are documented in Cruz et al.(2003), Cruz et al. (2004), Cruz et al.(2005).

Transfer Learning with PyTorch

PyTorch applies transfer learning with PyTorch to classify aerial photos according to the fire danger they convey using only image details. The MODIS (Moderate Resolution Imaging Spectroradiometer) fire dataset established known fires in California from 2018 to 2020. The MODIS dataset contains high-resolution imagery and labeled map regions for a given date range to gain insights into past locations of wildfires. The images were sampled from the prior two-year period, 2016 to 2017, in areas within and near the established future fire regions. Transfer learning is used to adapt a pretrained "ResNet 18" model (which was not previously trained on aerial photos) supplemented with a couple of hundred images labelled as "Fire" and "NoFire." Fine-tuning a pretrained model (originally trained on the ImageNet dataset) for use with aerial photos is an effective approach for extracting meaningful information from these images in the context of forest fire prediction. The ResNet architecture, with its deep layers and skip connections, has proven effective in various computer vision tasks, including object recognition and image classification. With this approach, only a couple of hundred images are needed and about 15 minutes of CPU time to build an accurate model. Model accuracy is currently about 89%, but might be improved with more iterations, a larger set of images, and more focus on regularization. Aerial photos covering 60 square miles can be ingested by the model to make accurate Fire/NoFire predictions. (Chesebrough 2023)

WRF-Fire

A wildland fire-behavior module WRF-Fire is integrated into the Weather Research and Forecasting (WRF) public domain numerical weather prediction model. The fire module is a surface fire-behavior model that is two-way coupled with the atmospheric model. Near-surface winds from the atmospheric model are interpolated to a finer fire grid and are used, with fuel properties and local terrain gradients, to determine the fire's spread rate and direction. (Coen et al. 2013)

FLogA

FLogA (Fire Logic Animation) is a set of methods and an interactive, web-based, user-friendly software tool which allows the user to draw a forest area on the map anywhere in Europe, insert fire ignition points, generate on the fly all input data layers required for a wildfire simulation, and then simulate and animate the behavior of the evolving fireline under different weather conditions. FLogA utilizes only publicly available non-proprietary data, software libraries and Web services. It adopts a distributed, open, service oriented architecture that is easy to maintain and extend. Wind, as the most dynamic parameter affecting a wildfire's behavior, can be sampled around a reference direction and speed value reported by the closest METAR station, to generate multiple simulation scenarios. FLogA generates informative interactive geo-animations of simulation results with color representing a fire property of interest, such as the flame length or the forest cells burn probability, while the terrain of the forest in the background may be colored according to a characteristic of the forest (e.g. elevation, land cover, etc.). Geo-animations allow the user to "fly-over" any part of the affected terrain as the fire is progressing. In addition, FLogA offers drawing tools for editing the forest's spatial properties (e.g. change fuels, define cleanings zones etc.) to generate alternative "what-if" simulation scenarios. Furthermore, it can be set to automatically monitor any

European forest area and trigger fire simulations as soon as “hotspots” are posted on the Internet by satellite services. (Bogdos, Manolakos 2013).

Prometheus

Prometheus is a deterministic fire growth simulation model that was developed to help fire managers to understand the probable consequences of their decisions. It uses spatial input data on topography (slope, aspect, and elevation), fuel types, and weather to simulate fire growth by applying Huygens’ principle of wave propagation to the rate-of-spread predictions from the Canadian Forest Fire Behavior Prediction System of the Canadian Forest Fire Danger Rating System. This approach produces detailed fire perimeters at user-specified display time step intervals. Each active vertex along the perimeter has corresponding fire behavior output. Exported fire perimeters are compatible with geographic information systems. Additionally, three interpolation techniques are available to produce optional raster fire behavior outputs. (Tymstra et al. 2010)

Prometheus integrates fire science, mathematics, and computer software engineering. The Fire Behavior Prediction System is used to predict the physical characteristics of a wildfire at many points around the fire perimeter, including the underlying rates of spread for the spatial simulation of firefront propagation. Wave propagation equations provide a mathematically tractable approach to simulate the complex geometry of an expanding fire perimeter over a long period of time in a heterogeneous environment. Computer programming and simulation modeling allow the model to be implemented at high spatial and temporal resolution through the performance and management of millions of calculations. (Tymstra et al. 2010)

Prometheus has also proven effective in assessing communities’ fire risk and in the design of FireSmart community plans. The strength of the Prometheus model lies in its flexibility, which allows users to change the fire environment inputs and to integrate the model with other applications such as Burn-P3. (Tymstra et al. 2010)

Prometheus COM (Common Object Model) is Microsoft Windows programming standard that allows object-oriented COM components (Dynamic Link Libraries) to be re-used in different software applications and languages without sharing source code. Prometheus uses this component-based software architecture. The important principles of COM include: reuse of the component objects, interoperability of the binary standard, allowance for distributed capabilities. Prometheus is engineered using five separate COMs. These COMs are called low-level interfaces and include: FuelCOM, FWICOM, GridCOM, FireEngine, WeatherCOM. To facilitate the use of these low-level interfaces, an umbrella or wrapper COM was developed. This high-level interface is called PrometheusCOM. It provides a more user-friendly interface for programmers to communicate with the low level COMs. (FireGrowthModels.ca 2022)

Burn P3

Burn-P3 (probability, prediction, and planning) is a spatial fire simulation model that is used for land-management planning and wildland fire research. It uses the Prometheus fire-growth engine to simulate the ignition and spread of a very large number of fires. The inputs to Burn-P3 consist of fuels (e.g., vegetation), topography, weather, and patterns of fire ignitions. Its main output is a surface of fire probabilities, or burn probability map. (FireGrowthModels.ca 2023)

It is a Windows-based software application, which computes burn probabilities for large landscapes, produces additional outputs, such as fire intensity maps and extracts fire statistics and simulated fire perimeters. The lead agency, custodian and legal intellectual property rights holder of Burn-P3 is the Canadian Forest Service.

The last version is the Burn-P3 ver. 4.7 (NRC 2017).

FireFamily+ (FF+)

FireFamily+ is a software package used to calculate fuel moistures and indices from the US National Fire Danger Rating System (NFDRS) using hourly or daily fire weather observations primarily from Remote

Automated Weather Stations (RAWS). NFDRS use is mandated for fire preparedness and response decisions by all Federal and most State agencies and is operationally run with USFS FAM Weather Information Management System (WIMS). (Bradshaw and McCormick 2000)

FF+ has several subsystems. First, it provides all the necessary model calculations to produce fuel moistures and fire danger indices for the NFDRS 1978, 1988 and the newly added NFDRS2016 and well as the Canadian Forest Fire Danger Rating System and the Fosberg Fire Weather Index. When using appropriate hourly fire weather data, usually provided in an FW13 text format, the system can calculate hourly Nelson dead fuel moistures, daily Growing Season Index-based live fuel moistures and all associated fire danger indices such as the Energy Release Component, Burning Index, Spread Component and Ignition Component as part of the new NFDRS2016. Second, the system includes the ability to compare fire danger indices to agency fire reports and use this information to establish breakpoints for decision making on local units. Finally, FF+ includes a suite of climatological tools to explore and display seasonal variations in fire danger to better access and communicate conditions as they change throughout a fire season or from year-to-year. (Bradshaw and McCormick 2000)

This tool is constantly improved by developers of the US National Fire Danger Rating at the USFS, RMRS, Missoula Fire Sciences Laboratory in collaboration with developers from Altura Solutions.

Uses of FireFamily+ include: to compute indices and components of the National Fire Danger Rating System (NFDRS), and the Canadian Forest Fire Danger Rating System from weather climatology data; to summarize weather climatology to produce climatological breakpoints for fire management decision making; combining the fire occurrence record in the analysis displays the historical relationships between weather conditions and increasing fire occurrence which can be used to set fire business thresholds and track seasonal progression of Fire Danger; analysis of specific weather information helps in estimating fire potential for an ongoing fire’s continued growth.

FIREMON

Fire Effects Monitoring and Inventory System (FIREMON) is an agency independent plot level sampling system designed to characterize changes in ecosystem attributes over time. FIREMON consists of standardized sampling methods and manuals, field forms, database, analysis program, and an image analysis guide so that fire managers can 1) design a fire effects monitoring project, 2) collect and store the sampled data, 3) statistically analyze and summarize the data, 4) link the data with satellite imagery, and 5) map the sampled data across the landscape using image processing. FIREMON allows flexible but comprehensive sampling of fire effects so data can be evaluated for significant impacts, shared across agencies, and used to update and refine fire management plans and prescriptions. FIREMON has a flexible structure that allows the modification of sampling methods and local code fields to allow the sampling of locally important fire effects evaluation criteria. It is a Desktop application created for computers running Windows 98, ME, 2000, XP, 7, 8 and 10 operating systems. The system was developed by the U.S. Forest Service, Missoula Fire Sciences Laboratory in cooperation with the U.S. Geological Survey, National Park Service and Systems for Environmental Management. Funding was provided by the Joint Fire Science Program. (Lutes et al. 2006)

FOFEM

FOFEM (a First Order Fire Effects Model) is a computer program for predicting tree mortality, fuel consumption, smoke production, and soil heating caused by prescribed fire or wildfire. First order fire effects are those that concern the direct or indirect or immediate consequences of fire. First order fire effects form an important basis for prediction secondary effects such as tree regeneration plant succession, and changes in site productivity, but these long-term effects generally involve interaction with many variables (for example, weather, animal use, insects, and disease) and are not predicted by this program. FOFEM is used by resource managers and planners to provide quantitative fire effects information for tree mortality, fuel consumption mineral soil exposure, smoke and soil heating. FOFEM input files can be created in the FFI ecological monitoring software or by manually creating an input file in FOFEM's standard format. (FireLab.org)

SpatialFOFEM is a spatial implementation of the point-scale FOFEM model that simulates two sets of outputs: 1) Fuel Consumption & Smoke Emissions using a GeoTIFF of fuels (typically FCCS fuel beds) and 2) Fire-caused Tree Mortality using a GeoTIFF tree list (typically from the TreeMap (Riley, et al 2022). Outputs are GeoTIFF files. SpatialFOFEM Fuel Consumption & Smoke Emissions are available in FlamMap 6.2. (FireLab.org)

Fire Effects Information System (FEIS)

FEIS is an online collection of reviews of the scientific literature about fire effects on plants and animals and about fire regimes of plant communities in the United States. FEIS reviews are based on thorough literature searches, often supplemented with insights from field scientists and managers. FEIS provides reviews that are efficient to use, thoroughly documented, and defensible. Approximately 15 to 30 new or revised reviews are published in FEIS each year. There are 3 types of FEIS reviews (Zouhar 2015):

1) Species Reviews include information on plant, lichen, and wildlife species' life history, ecology, and relationship to fire. They are available for more than 1,200 species occurring throughout the United States.

2) Fire Studies are summaries of one or more fire research projects at a specific location. Only research that provides detailed descriptions of site characteristics, burning conditions, fire behavior, and fire effects is included in Fire Studies. FEIS contains more than 150 Fire Studies, which complement Species Reviews and provide information on hundreds of species for which a Review is not available.

3) Fire Regime Syntheses provide up-to-date information on fire regimes of ecosystems in the United States. The syntheses provide information from the literature and from LANDFIRE data on historical fire frequency, spatial pattern, extent, and seasonality; historical ignition sources; typical patterns of fire intensity and severity; and contemporary changes in fuels and fire regimes. The detailed analysis in Fire Regime Syntheses supplements the information in Species Reviews and provides fire regime information on plant communities.

The Fire Effects Library houses the literature that supports FEIS reviews. The library contains more than 61,000 references on fire effects and the general biology and ecology of organisms in North America. References are catalogued in an online database, the Citation Retrieval System (CRS). To add to the library, FEIS staff regularly search scientific abstracts, literature databases, and tables of contents from refereed English-language scientific journals and government publication lists. Other library acquisitions include theses and dissertations, conference proceedings, and unpublished reports. A link to the list of scientific literature routinely searched is provided below. Users are encouraged to use CRS to supplement information from FEIS reviews. Managers from several land management agencies (United States Department of Agriculture, Forest Service, and United States Department of Interior, Bureau of Indian Affairs, Bureau of Land Management, Fish and Wildlife Service, and National Park Service) choose the species included in FEIS. These agencies funded the original work and continue to support enhancement and maintenance of the database. (Zouhar 2015)

ArcFuels

ArcFuels was built to streamline the fuel management planning process and provides tools for quantitative wildfire risk assessment. ArcFuels is a toolbar implemented in ArcMap which creates a trans-scale (stand to large landscape) interface to apply pre-existing forest growth (e.g., Forest Vegetation Simulator) and fire behavior models (e.g., FlamMap) to aid in vegetation management, fuel treatment planning, wildfire behavior modeling, and wildfire risk assessments. The ArcMap framework helps users incorporate data from a variety of sources to address project-specific issues that typify many fuel treatment projects. ArcFuels was built to accommodate ArcGIS raster data (such as LANDFIRE data) and/or forest inventory data. ArcFuels provides a logical flow from stand to landscape analyses of vegetation, fuel, and fire behavior, using a number of different models in a simple user interface within ArcMap (Rocky Mountain Research Station 2014). It is available online: https://www.fs.usda.gov/research/rmrs/projects/arcfuels

Wildland Fire Assessment System (WFAS)

WFAS is an internet-based information system. The current implementation provides a national view of weather and fire potential, including national fire danger and weather maps and satellite-derived "Greenness" maps (Burgan et al. 1997). Development is continuing. WFAS was first made available in 1994. In 1999 operation was transferred from the Fire Sciences Laboratory (FS Rocky Mountain Research Station, Missoula, Montana) to the National Interagency Fire Center (NIFC, Boise, Idaho). WFAS was redesigned in 2002 to provide easier access to products and vastly improve the archival process. The archives now provide real-time access to past map images including fire danger, heavy fuel moisture, Haines Index, and greenness. The navigation bar on the left organizes products by category. Selection provides access to links along with a description of the product. The Quick Links table provides direct access to products, which are categorized as Current conditions, Forecast, Image archive (just pictures), Data archive. Archives are selected from a calendar. Variables available for each day are listed. (WFAS 2023)

The Fire Potential / Danger module consists of Fire Danger Rating, Dry Lightning and Lightning Ignition Efficiency. The Weather module is composed of Fire Weather, Google Earth Map Data, Map Data. The Moisture / Drought module provides information on Dead Fuel Moisture, Growing Season Index, Keetch-Byram Drought Index and National Fuel Moisture Database. The Static Maps represent the Fire Weather Stations and NFDRS Fuel Models. (WFAS 2023)

WFDS

The Wildland-Urban Interface Fire Dynamics Simulator (WFDS) is an extension of NIST's structural Fire Dynamics Simulator (FDS) to fuels that include vegetation. WFDS is a tool that uses computational fluid dynamics (CFD) models to solve the governing equations for buoyant flow, heat transfer, combustion, and the thermal degradation of vegetative fuels. The solution method makes use of large eddy simulation techniques to solve the gas-phase equations on computational grids that are too coarse to directly resolve the detailed physical phenomena. The Wildland-Urban Fire Dynamics Simulator is intended to help understand the interactions between fire in the wildlands and how it behaves differently when encountering a developed area. The physics of this change in fire behavior is the focus of this project, and this understanding may lead to the ability to design communities better able to withstand an approaching wildfire. (Pacific Northwest Research Station 2018)

The procedure for running WFDS is the same as for Fire Dynamic Simulator (FDS). WFDS currently has two versions: Fuel Element Model for fuel in a specific volume, e.g. in the crown of a tree, and Boundary Fuel Model for surface fuel, e.g. grass. (Pacific Northwest Research Station 2018)

It is currently capable of describing the spread of a fire on a flat surface - a grass fire and the burning of a single tree. The aim of the development is to improve the system to be able to simulate a fire within larger vegetation and more complex topography.

PHOENIX Rapidfire

PHOENIX predicts the potential progression of fire across virtual landscapes under different weather and fire suppression scenarios (Tolhurst, 2008; Duff et al., 2018). PHOENIX was developed from 2003 to rapidly replicate the manual prediction process, accounting for changes in the weather, patterns in fuel, the efforts of firefighters and the effect of varying topography. The simulation implements a fire characterization model capturing details such as flame height, intensity, size, ember density, spotting and convection throughout the simulation process. Such fire predictions can help identify the potential threat to homes and buildings and indicate the likely arrival times of fire. Rapid predictions can help provide more timely warnings to communities, aid evacuation planning and help guide firefighting efforts. (Flare Wildfire Research 2023)

PHOENIX is widely used by management agencies (see e.g. Thwaites 2015) in southern and eastern Australia for operational fire predictions (during an event) and for fire risk modelling (prior to the fire season). Outputs from PHOENIX are used to support investment decisions, positioning of fire resources during a fire and evacuation decision making. PHOENIX is now managed by Fire Predictive Services. (Flare Wildfire Research 2023)

Aurora

AURORA Fire Behavior Calculator calculates Fire Behavior Index, Rate of Spread and other behavior variables using published models for Australian vegetation, aligns with Australian Fire Danger Rating System. The calculator ingests the Bureau of Meteorology's ADFD™ forecast gridded weather into models for user`s personalized locations. The fire behavior models are from Cruz et al. 2015.

HIGRAD/FIRETEC

FIRETEC uses a multi-phase transport model, based on the ensemble-averaged conservation equations for mass, momentum, energy, and chemical species. FIRETEC, which can be used for solution of two- or three-dimensional problems, couples models for macroscale effects of processes such as combustion, radiation, convective heat exchange, and aerodynamic drag in order to achieve an entirely self-determining coupled atmosphere–fire model. The physical and chemical formulations of FIRETEC are described in detail by Linn (1997), with several modifications given by Linn et al. (2002). FIRETEC is entirely physics-based and therefore self-determining rather than empirical. It is coupled with an atmospheric model called HIGRAD (Reisner et al. 2000), so as to describe the dynamics of wildfires in a fully three-dimensional configuration under arbitrary meteorological conditions with large variations in terrain and vegetation type and distribution (Linn et al. 2002). This approach accounts for the transport of temporally and spatially varying atmospheric species (i.e., oxygen), and includes the treatments of turbulence and chemistry necessary to account for energy production and transport (both advective and radiative) and fuel depletion, in the presence of self-determining variations of wind speed and direction (both local and mesoscale).

FireStation

FireStation is an integrated software system for the numerical simulation of fire spread on complex topography. FireStation software was developed under the environment of the CAD application Microstation. It was written in MDL, a specific C language of Microstation that has built-in subroutines for the design of window-based interfaces, generation of visualization elements in the 3D space, on top of the usual mathematical capabilities of the C language. The wind models are self-contained Fortran codes, which run as external programs. It applies a simple ellipse as the underlying template to shape fire growth. Fire shape is described with recourse to an ellipse-type model. Two different models are implemented for the simulation of the wind field. Both these models predict wind velocity and direction based on local observation taken at meteorological stations. The FireStation system for decision support is made up of three modules that are interdependent relatively to the flow of information. The hierarchical organization is the following: 1. Wind Speed Module, 2. Fire Danger Rating Module, 3. Fire Spread Module. The whole system was developed under a graphical interface, aiming at a better ease of use and output readability so as to facilitate its application under operational conditions. (Lopes et al. 2002)

FIREMAP

FIREMAP is a simulation system designed to estimate wildfire characteristics in spatially non-uniform environments and simulate the growth of fire in discrete time steps. This simulation system integrates Rothermel's behavior prediction model (Rothermel 1972) with a raster- based geographic information system. The outputs can be displayed as digital maps. (Vasconcelos and Guertin 1992)

QGIS Fire Mapping Tool

The QGIS Fire Mapping Tool (FMT) was developed to address the needs of users who may need to determine the effects of small fires that are below the MTBS burned area threshold, or who cannot wait for an MTBS assessment to be published. It facilitates the identification and processing of Landsat imagery that correspond to a user-specified area of interest, generates fire perimeters, and performs thresholding of the Landsat imagery to produce burn severity images. Through the use of this tool, users can employ satellite-based imagery and derivative information to produce their own burn severity assessments. QGIS FMT mimics the original Event Mapping Tool (EMT) developed by the U.S. Forest Service Geospatial Technology and Applications Center. This tool is fully open-source and is freely distributed. (MTBS 2023)

FSim-Wildfire Risk Simulation Software

FSim simulates the growth and behavior of hundreds of thousands of fire events for risk analysis across large land areas using geospatial data on historical fire occurrence, weather, terrain, and fuel conditions. Effects of large fire suppression on fire duration and size are also simulated. The purpose of this research is to develop a practical method of quantifying geospatial wildfire impacts, including annual probabilities of burning and fireline intensity distributions at any point on the landscape. The distribution of intensity can be combined with assets or values (e.g. homes, habitat, watersheds) using their susceptibility at each intensity level to perform quantitative geospatial risk analyses. Geospatial analyses can also depict: annualized expected impact of fire on values or assets; fire size distributions and geospatial event sets (polygons of all simulated fires); transmission of fire from the start locations to the points of final impact; summaries of wildfire transmission: defining a “fireshed” – the surrounding area that a fire can start and affect a particular location or asset and a “fireplain” – the areas that can be affected by fires starting in a given location; changes in risk resulting from fuel management activities (e.g. prescribed burning). (Missoula Fire Sciences Laboratory 2023)

The FSim simulation process involves the following: 1. Assembly of geospatial landscape and terrain data, typically from LANDFIRE 2. Assembly and processing of historical fire occurrence data (Fire Occurrence Database) 3. Assembly and processing of historical weather observations (WIMS, FireFamilyPlus) Using these datasets, the weather data are analyzed to produce a large number of synthetic ‘years’ comprising daily weather sequences. For each day in each year the ignitions are stochastically generated and the growth and behavior of resulting wildfires are simulated as they burn across the landscape. The process continues for the specified number of years, which produces a probability distribution of intensities. These can be summed to obtain the annualized burn probability. The user must calibrate the model results by comparison with observed fire distributions. (Missoula Fire Sciences Laboratory 2023)

FSim is used at national scale with relatively coarse resolutions (270 m) and regional or local scales with relatively fine resolutions (e.g. 90 m). It is period updated with improved algorithms and features.

Wildland Fire Decision Support System (WFDSS)

WFDSS is used for real-time incident decision making and documentation and providing a spectrum of risk-based functionality, including operational risk assessment, probabilistic fire spread modelling and exposure assessment. A related quantitative wildfire risk assessment framework is built on common approaches for hazard and exposure assessment, but incorporates vulnerability through the characterization of fire effects as a function of fire intensity, and integrates risk metrics across various resources and assets by accounting for the relative importance through multi-criteria analysis. (Wildland Fire Decision Support System 2023)

According to McEvoy et al. (2021), the framework has some notable limitations; for instance, a poor ability to account for fire impacts that play out over different time scales and the typical use of expected values masks low-probability high-consequence events.

FROST Family

FROST Family is a risk-based fire regime simulator for assessing the impacts of fire and land management on human and environmental values across landscapes. It is composed of: FROMAGE – a data preparation program; FROST – a fire regime simulator; FRAPPE – a fire impact processor.

FROST combines fire event simulation tools with Bayesian networks to represent uncertainty in the underlying processes. The model simulates fire regimes over decades to centuries. The FRAPPE software allows to calculate and analyze how fire (simulated by FROST) impacts different landscape values. These landscape values are represented by a number of post-processors which contain extra data and modelled algorithm(s). Each post processor utilizes the FROST fire data to calculate impact on its value of interest. Values of interest include: 1) Biodiversity (including ecological fire groups, Wet forest, ecological refuges, Leadbeater possums and Greater Gliders); 2) Carbon; 3) Infrastructure loss (e.g., roads, powerlines, industrial building, hospitals); 4) People and House loss; 5) Geometric Mean of Species Abundance; 6) Shannon's diversity and Fractal dimension index; 7) Soil Erosion Rates; 8) Major Water Contamination Events.

2.3.3.3 Assessment of relevant tools

A summary assessment of tools employed for fire behavior analysis is provided in appendix 5.3 (Table 48).

Dynamic models, i.e., models that calculate the forces causing motion (in contrast to kinematic models that calculate rate of motion without regard to the forces causing it), are necessary to represent the exchange of forces between the atmosphere and fire (Coen 2011) and to uncover the physical basis for fire phenomena. Kinematic models, which are the most prevalent type used in wildland fire modeling, e.g., FARSITE (Finney 1998), BehavePlus (Andrews et al. 2008), and Prometheus (Tymstra et at. 2010), have been widely applied in estimating rates of spread of fires in various terrain, fuel, and wind conditions—in particular, when quick estimates are needed in field applications. Their limitations appear in attempts to apply them beyond estimates of the rate of spread to anticipate changes of behavior arising from fire-generated winds, dynamic interactions such as blowups, interactions between multiple fires, and fire phenomena such as fire whirls. For these issues that involve the exchange of forces between the fire and the atmosphere, dynamic models are required. By isolating the fire's effects on the atmospheric environment, a previous study (Coen 2005) showed that the fire's impact on the ambient wind velocity can be as great as several meters per second even 5 km away, can create on the order of 10° of buoyancy near the surface, and, in the case of large fires, can possibly become the dominant weather event in its vicinity.

According to Bogdos and Manolakos (2013), BehavePlus has been developed mainly for educational purposes. It attempts to avoid simulation setup complexity, e.g. using spatial data, and cannot be used to describe a real fire event. FlamMap (Finney 1999) adds the spatial component, allowing conditions to vary in different areas of the forest. It takes as input detailed spatial information for the forest area: slope, aspect, fuel models and canopy cover, and produces static maps of fire line characteristics, e.g. fire line intensity. FARSITE (Fire Area Simulator) adds the temporal component, allowing conditions to vary during the simulation period. It requires the same spatial information as FlamMap but also needs temporal weather data layers. WFDSS (Wildland Fire Decision Support System) (Noonan-Wright et al. 2011) uses the FSPro (Fire Spread Probability) simulator, which introduces probabilistic fire spread from a known perimeter or point based on multiple FARSITE simulations and historical weather sequences derived from Remote Automated Weather Stations (RAWS). Although the wildfire simulation tools described above are complete and mature, they are also quite complicated for untrained users since they require setting up a large number of difficult to obtain GIS (Geographical Information System) input files. These GIS files have also to be co-registered, with identical resolution, extent, projection and datum. Their scope is mainly long-term strategic decision support, and they are therefore difficult for a non-fire behavior specialist to setup and use. Moreover, they do not provide ways for the user to introduce, in an interactive and graphical manner, possible human interventions to the forest's spatial characteristics, e.g. perturbations to the fuel models, in order to create "what-if" simulation scenarios, making again the parallel use of GIS platforms a necessity.

2.4 M22: Models for canopy fuel load estimation

2.4.1 Introduction

One of the main variables for crown fire behavior modeling is the available canopy fuel load (***CFL*** in kg per m^2) at stand level. This variable is necessary for the estimation of the heat release at the flaming front and the estimation of the canopy bulk density (***CBD*** in kg per m^3), which, in turn, is determined by the total amount of the canopy fuel mass per unit canopy volume (Scott and Reinhardt 2001).

The Canopy fuel load (*CFL*) is defined as the canopy fuel mass per unit ground area (Scott and Reinhardt 2007). However, during a wildfire only a portion of the total canopy biomass is usually consumed by the flaming front, consisting by the thinnest parts of the canopy including both, foliage and branches. Van Wagner (1977) suggested that conifer needles are the main aerial fuels that are consumed during a crown fire spread. In this sense, the available canopy fuel load equals to the total dry weight of the needles and the branches with diameter between 0.0 and 0.63 cm, following the suggestions by Stocks et al. (2004). On the contrary, Alexander et al. (2004) suggested to include pine needles, live branches between 0.0 and 1.0 cm, as well as dead branches of the same dimensions, under the available *CFL* definition for jack pine (*Pinus banksiana* Lamb.), and black spruce (*Picea mariana* Mill.) in Canada. Canopy Fuel Load can be calculated at tree level and at stand level. For modeling fire characteristics are used at sand level.

2.4.2 Relevant models

2.4.2.1 Canopy Fuel Load at tree level

In order to estimate the available canopy dry weight, destructive sampling of selected trees and oven-drying processes of canopy parts are currently conducted, creating significant problems from a practical point of view. In an effort to overcome this shortage, allometric models have been established for a number of flammable species across fire-prone ecosystems in South Europe and North America, as well. The modeling process for the prediction of the available *CFL* is mainly based on Ordinary Least Squares (OLS) theory, leading to reliable results in the most of the cases. Similar to the above-ground biomass (AGB) modeling, the most fitted nonlinear form is the power model, defined as $\boldsymbol{y=ax^b}$ (Huxley and Teissier 1936). In order to stabilize the residuals across the whole range of the fitted values, a log-log transformation is usually performed, leading to a simple linear form where all the assumptions are met. At the final stage, the inherent bias of the back-transformation is avoided through the multiplication with a correction factor (CF), defined as (Baskerville 1972):

$$CF = \exp\left(\frac{SEE^2}{2}\right)$$

However, several relevant research used weighted nonlinear regression as an alternative to the previous analysis, leading to equally reliable results.

2.4.2.2 Regressors

The main predictor during the *CFL* modeling is the stem's Diameter at Breast Height ($DBH_{1.30}$ or ***DBH*** in cm), explaining the largest part of the *CFL* variance at tree level. The implementation of the specific regressor presents some clear advantages during crown fire modeling, since the *DBH* is included in all forest inventories and management plans as primary information at tree level. Furthermore, it can be easily and accurately estimated in field conditions based on the use of a conventional or a digital hand caliper.

The total tree height (***H*** in meters) is assumed to improve the *CFL* predictions as an additional regressor, but its estimation presents some difficulties during fieldwork due to the dense canopy or the dense understory vegetation. It represents the vertical distance between the top and the tree base. The *H* is not always available in forest management plans and inventories, since a small sample of tree heights at stand level is usually needed for the stem volume estimation. Accurate height-diameter models may rectify this shortage, thus presenting an alternative solution to *CFL* modeling procedure.

The crown width (***CW*** in meters) is another potential predictor of the *CFL* at tree level, which has been successfully used in allometric models. It represents the average horizontal diameter of the crown usually at two vertical directions under the assumption of an almost circular-shaped crown. The *CW* is mainly defined by the competition status within a stand (Krajicek 1961), delimiting the available tree's growing space. Usually, data regarding this tree variable are not available and relevant models are currently used. In the absence of *CW* models at species basis, the estimation of the dependent *CFL* becomes a difficult task.

The length of the live crown (***CL*** in meters) is another independent variable for the *CFL* prediction. It can be directly estimated in the field using a laser or an ultrasound device or it can be estimated through the difference between the *H* and the crown base height (***CBH*** in meters). The *CL* modeling is a reliable solution and some reputable models have been proposed in the forestry literature. Some authors have used as a dependent variable the crown ratio (***CR*** dimensionless with values between 0 and 1) instead of the *CL*, which leads to accurate estimations of the *CL*.

The age (***t*** in years) of a tree is the absolute age of a living tree. For pine species, it can be estimated using an increment borer approximately at the breast height by adding 5 - 7 years, which corresponds to the time-space needed for a tree to become 1.3m in height. For other species, the age can be estimated accurately through destructive sampling.

The model's simplicity is one significant factor that must be considered when selecting a model for *CFL* estimation. The introduction of additional variables into the model may increase its predictive power, but serious problems may arise due to the potential lack of relevant data or the absence of additional models at species basis. Despite the wide range of allometric models for the prediction of dendrometric characteristics at the tree level for a significant number of forest species, there is still a gap in the world literature, and additional work is currently needed.

2.4.2.3 Canopy fuel load at stand level

Currently, two methods are applied in order to estimate the available *CFL* at plot, stand or at sector level. The ordinary method is based on allometric relationships between tree fuel load and one or more independent variables. This implies that a significant amount of data are available, for example the *DBH* of all trees within a well-defined spatial entity (unit), and the fuel load is estimated for each tree separately. The available CFL_{stand} is calculated afterward by summing the CFL_{tree} and dividing it by the total area of the spatial unit.

The advanced method is based on statistical models in an effort to predict the CFL_{stand} directly from stand parameters. Those parameters usually reflect the competition status within a stand, the development stage of the tree species, or the quality (productivity) of the site. The most common independent variables at stand level are explained below.

- Number of stems per hectare (***N***). It is the most common variable in forest management and it is very easy to be estimated in field conditions. It is expressed as the number of living trees per unit area (ha) with large variability, depending on the species, the development stage (age) of trees and the management regime. The range of the specific variable is between 70 and 2500 stems per hectare.
- Basal Area (***G*** in m^2/ha). The tree basal area (***g***) is defined as the cross-sectional area of a tree stem measured at breast height (1.30m). Under the assumption of a circular stem, the i^{th} tree basal area is

$$g_i = \frac{\pi}{4} DBH_i^2$$

Were DBH is the diameter at breast height (1,30 m)

Hence, the basal area at stand (*j*) level (*G*) of *n* trees is

$$G_j = \sum_{j=1}^{n_i} g_{ij}$$

The G can range between 10 and 100 m^2/ha, depending on the stand density.

- The Reineke's Stand Density Index (***SDI*** -), is a distance-independent measure of relative stand density and it is expressed as:

$$SDI = N\left(\frac{D_q}{25.4}\right)^b$$

Where N = trees/ha, Dq = quadratic mean diameter (cm), b = exponent of Reineke's equation, often reported to equal 1.605

Dq (in cm) is expressed as:

$$D_q = \sqrt{\left(\frac{G}{0.0000785N}\right)}$$

The SDI can range from 100 to 2500 and the Dq from 10 cm to 50 cm, without precluding any values beyond that range.

- Dominant height (***H_0***– in meters) is defined as the mean height of the 100 thickest trees per hectare, or equally proportional. For example, when working with fixed radius plots of 1000m^2, the mean height of the 10 thickest trees equals approximately to the *H_0*. It is used to estimate the Site Index of a forest site (productivity measure). It can be ranged from 10 m up to 30 m, depending from the tree species.

- The Relative Spacing Index (RSI – dimensionless). It is defined as the average distance between trees divided by the average height of the dominant canopy, according to the following function (Burkhart and Tomé 2012):

$$RSI = \frac{\sqrt{\left(\frac{100000}{N}\right)}}{H_0}$$

The *RSI* can be ranged between 0.1 and 0.5 for some conifer species such as the Black pine (*Pinus nigra* Arn.).

From a modelling perspective, the advanced method provides some notable superiority since it leads directly to *CFL_{stand}* predictions using primary variables as inputs. The limited use of this method is attributed to the lack of similar models for the majority of forest species.

2.4.2.4 Overview of relevant models

The basic method for the CFL estimation is through destructive sampling, where a sample of trees is selected and the dry weights of the target components of each tree are determined. In the following phase, the partial dry weights are related with easily estimated morphological attributes at tree or at stand level such as the diameter at breast height (*DBH*) or the basal area correspondingly, and statistical equations (or allometric models) of high prediction accuracy are developed. In addition, the statistical power of the nonlinear models has been increased and the proposed models fulfill all the required assumptions. Recently, remote sensing methods have been widely used for the estimation of the CFL, but they are based on the same equations too, during the fieldwork or during the ground checking procedure. Hence, the most comprehensive up to now are considered the allometric equations in terms of the accuracy of the results and the easiness of their use. In most cases of managed forests already exist measurements of the data needed, such as Basal Area, for the calculation of CFL and CBD. Since allometric equations are based on statistical methods, they are valid for the species that they are made for. For this reason, specific equation must be used for the calculation of CBD for each species.

The tables that follow (Table 5 - Table 7) provide the allometric equations for the most vulnerable to fire species available in the literature, along with the description of the independent variables, the tree species the equations are valid for, the data origin (location) for the development of the model, as well as the dimensions of the available fuels. Because allometric equations are simple models that can relatively easily be developed into software tools, the existing relevant software tools are not considered in this chapter. Moreover, it is not possible to provide a comparative assessment of these models, since each one is valid for a specific (vulnerable to fire) species.

Table 5: Allometric models for total fuel load of dry weight (kg) at tree level for of fire-prone species. All these models have validity to the tree species they are referred to.

Model [M22.A.**XX**]		**Valid for tree species**	**Location (Country)**	**Model for Active Fuels (foliage and thin branches) in kg of dry weight**		**Reference**
1		*Pinus halepensis*	Greece	Foliage	$Y=0.02539DBH^{1.811}$	Mitsopoulos and Dimitrakopoulos 2007
				Branches (0.0-0.63)	$Y=0.00617DBH^{2.129}$	
2	2a	*Pinus brutia*	Turkey	Both, foliage and branches (0.0-0.63)	$Y=-3.409773+0.691057DBH$	Baysal 2021
	2b			Both, foliage and branches (0.0-0.63)	$\ln Y = 5.838 + 1.195\ln CW + 0.661\ln CL$ $CF=1.0927$	Küçük et al. 2008
3	3a	*Pinus nigra*	Turkey	Both, foliage and branches (0.0-0.63)	$Y=0.125196H^{1.949}$	
	3b			Both, foliage and branches (0.0-0.63)	$\ln Y = 5.266 + 1.368\ln CL + 0.936\ln CW$ $CF=1.2104$	
4		*Eucalyptus globulus*	Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=0.01258DBH^{1.705}+0.02949DBH^{1.917}$	Dieguez-Aranda et al. 2009
5		*Eucalyptus nitens*	Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=0.0053DBH^{2.393}+0.000922DBH^{2.632}$	Dieguez-Aranda et al. 2009
6	6a	*Pinus pinaster*	Iberian Peninsula	Both, foliage and branches (0.0-0.63)	$Y=0.0117DBH^{1.9356}CL^{0.4836}+0.0031DBH^{1.5463}t^{0.5238}$	Jiménez et al. 2013
	6b		Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=0.005DBH^{2.383}+0.00188DBH^{2.154}$	Dieguez-Aranda et al. 2009

	6c		Spain	Both, foliage and branches (0.0-0.63)	$Y= 0,01566DBH^{2,072} + 0,007241DBH^{1,789}$	Gómez-Vázquez et al. 2013
7		*Pinus pinea*	Spain	Both, foliage and branches (0.0-0.63)	$Y=-4.829+0.747DBH+0.611CW^{2}$	Molina et al. 2011
8	8a	*Pinus contorta*	Canada	Both, foliage and branches (0.0-1.0)	$Y= 0.0672H^{1.6934} + 0.0551H^{1.9870} + 0.1407H^{1.4847}$	Johnson et al. 1989
	8b			Both, foliage and branches (0.0-1.0)	$Y=0.1537H^{1.0263}CW^{0.8461}+0.0754H^{1.5752}CW^{0.6507}+0.3135H^{0.8873}CW^{0.7183}$	
9	9a	*Picea mariana*	Canada	Foliage	$Y=0.23317DBH^{1.25384}$	Alexander et al. 2004
	9b			Branches (0.0-1.0)	$Y=0.13267DBH^{1.11546} + 0.05553DBH^{1.12281}+0.04995DBH^{1.29626} + 0.000167DBH3.81224$	
	9c			Both, foliage and branches (0.0-0.63)	$Y=0.04923DBH^{2.08327}$	Stocks 1980
	9d			Foliage	$Y=0.00672DBH^{2.25699}$	Alexander et al. 2004
	9e			Branches (0.0-1.0)	$Y=0.00478DBH^{2.08881} + 0.00824DBH^{1.88877} + 0.00105DBH^{2.43234} + 0.00161DBH^{2.30592}$	
10	10a	*Pinus radiata*	Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=0.0423DBH^{1.714}+0.0078DBH^{1.961}$	Dieguez-Aranda et al. 2009
	10b		Spain	Both, foliage and branches (0.0-0.63)	$Y= 0.02023DBH^{1.899}$	Gómez-Vázquez et al. 2012

					$+ 0.01605DBH^{1.864}$	
11	11a	*Picea glauca*	Canada	Both, foliage and branches (0.0-1.0)	$Y= 0.24H^{1.5799} + 0.096H^{2.1078} + 0.0134H^{2.2123}$	Johnson et al. 1989
	11b				$Y=0.4316H^{1.1686}CW^{0.4874}+0.6376H^{0.83}CW^{1.4396}+0.1194H^{0.9312}CW^{1.282}$	
12		*Pinus sylvestris*	Galicia (Spain)	Foliage	$Y=1.1081DBH^{1.510}$	Dieguez-Aranda et al. 2009
13		*Quercus robur*	Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=1.379+0.01985(DBH^2H)^{0.7375}+0.00024DBH^2H$	Dieguez-Aranda et al. 2009
14		*Betula alba*	Galicia (Spain)	Both, foliage and branches (0.0-0.50)	$Y=0.03460DBH^{1.645}+0.03720DBH^{1.581}$	Dieguez-Aranda et al. 2009

<u>Note</u>: where Y is the CFL in kg, DBH is the diameter at breast height in cm, H is the total height in m, CW is the crown width in m, CL is the crown length in m, and t is the age in years.

Table 6: Allometric models for total fuel load of dry weight per square meter (kg/m2) at stand level for fire-prone species.

Model [M22.B.**XX**]		**Species**	**Country**	**Model for Active Fuels (foliage and thin branches) in kg/m² of dry weight**		**Reference**
1	1a	*Pinus halepensis*	Greece	Both, foliage and branches (0.0-0.63)	$Y=0.427+0.018G$	Mitsopoulos and Dimitrakopoulos 2014
	1b			Both, foliage and branches (0.0-0.63)	$Y= 0.187 + 0.028G$	Mitsopoulos and Xanthopoulos 2016
2	2a	*Pinus brutia*	Greece	Both, foliage and branches (0.0-0.63)	$Y= -0.483 + 0.003SDI$	Mitsopoulos and Xanthopoulos 2016
	2b		Turkey	Both, foliage and branche	$Y=0.001 +0.0000$	Küçük et al. 2021

				s (0.0-0.63)	$78SDI+0.00063N$	
3		*Pinus nigra*	Turkey	Both, foliage and branches (0.0-0.63)	$Y=0.00627+0.000799N+0.0001562SDI$	Küçük et al. 2021
4	4a	*Pinus pinaster*	Spain	Both, foliage and branches (0.0-0.63)	$Y=0.0119G^{0.9523}H_0^{0.3298}$	Fernández-Alonso et al. 2013
	4b		Turkey	Both, foliage and branches (0.0-0.63)	$Y=-0.01+0.0297G+0.0000681RSI$	Küçük et al. 2021
	4c		Spain	Both, foliage and branches (0.0-0.63)	$Y=0.02817G^{1.013}$	Gómez-Vázquez et al. 2012
5	5a	*Pinus radiata*	Spain	Both, foliage and branches (0.0-0.63)	$Y=0.0363G^{0.9401}$	Fernández-Alonso et al. 2013
	5b			Both, foliage and branches (0.0-0.63)	$Y=0.02862G^{0.9367}N^{0.04685}$	Gómez-Vázquez et al. 2012
6		*Pinus sylvestris*	Spain	Both, foliage and branches (0.0-0.63)	$Y=0.0597G^{0.8998}$	Fernández-Alonso et al. 2013
7		*Mixed Pine*	Spain	Both, foliage and branches (0.0-0.63)	$Y=0.0285G^{1.0146}$	Fernández-Alonso et al. 2013

8	*Pseudotsugamenziesii*	North America	Both, foliage and branches (0.0-0.63)	$\ln Y=-3.959+0.826\ln G+0.175\ln N$ $CF=1.0186$	Cruz et al. 2003
9	*Pinus ponderosa*	North America	Both, foliage and branches (0.0-0.63)	$\ln Y=-3.592+0.864\ln G+0.110\ln N$ $CF=1.0178$	Cruz et al. 2003
10	*Pinus contorta*	North America	Both, foliage and branches (0.0-0.63)	$\ln Y=-4.066+0.910\ln G+0.130\ln N$ $CF=1.0104$	Cruz et al. 2003
11	*Mixed* *Pine*	North America	Both, foliage and branches (0.0-0.63)	$\ln Y=-4.824+0.804\ln G+0.333\ln N$ $CF=1.0104$	Cruz et al. 2003

Where Y=CFL in kg/m^2, G the basal area in m^2/ha, N is the number of stems per ha, H_0 is the dominant height in m, SDI is the Reineke's Stand Density Index and RSI the relative Spacing Index.

Table 7: Additional models for H=tree height and CW estimation at tree level

Model [M22.C.**XX**]	**Species**	**Country**	**Allometric models for Pine species**		**Reference**
1	*Pinus brutia*	Greece	Crown Width	$CW=0.54825DBH^{0.71199}$	Raptis et al. 2022
2	*Pinus nigra*	Greece	Total height	$H=1.3+19.486(1-\exp(-0.086DBH))^{1.827}$	Raptis et al. 2021
3	*Pinus nigra*	Greece	Crown width	$CW=0.3459DBH^{0.7885}$	Raptis et al. 2018

2.5 M23: Models, methodologies and indices for fire risk assessment and fire damage estimation

2.5.1 Introduction

According to Chuvieco et al. (2023), the wildfire risk assessment is the process of merging information about three main dimensions: *hazard*, *exposure,* and *vulnerability*. With respect to wildfires, "fire risk" is defined as the probability of a wildfire occurring and its potential impact on a particular location at a particular time, and "hazard" is defined as any situation, process, material, or condition that can cause a wildfire or that can provide a ready fuel supply to augment the spread or intensity of a wildfire, all of which pose a threat to life, property or the environment. The vulnerability term includes a variety of sub-concepts and elements including sensitivity or susceptibility to damage, as well as reduced recovery and adaptation capabilities. Overall, the wildfire risk assessment represents the probability estimation about the time, the space, and the cause of a wildfire's onset and spread, the potential areas that will be affected, and the damages that will be probably caused.

Since the wildfire risk assessment is focused on the identification and distribution of the wildfire's potentiality in a given area, it integrates several factors to assess fire likelihood and potential impacts. Those factors include:

- *Weather conditions*. The temperature, the relative humidity, the wind speed, lighting activity, and the precipitation history affect wildfire's onset and propagation. In a wider frame of a climatic crisis, they determine the fire hazard and severity on at seasonal basis.
- *Topography*. Slope, aspect, elevation, valleys, and ridges may severely affect wildfire behavior and spread rate, precluding from a firefighting crew direct attack. In addition, the post-fire soil loss hazard is greatly dependent on the slope steepness factor.
- *Fuels.* The amount of available fuels for combustion their continuity, vertical or horizontal, their compactness status, and their composition determine critical characteristics of the flaming front, including flame length, frontline intensity, and fire residence time. It is worth noting that it is the only factor that can be modified through human interventions.
- *Human presence*. This factor is closely related to the likelihood of ignition, wildfire exposure, and vulnerability. Hence, it is a key factor during wildfire risk assessment.
- *Ecosystem services and ecological values*. Human and other living organism benefits generated by nature may be severely by fire, both directly and indirectly. Thus, it is critical to determine the potentiality of damage levels on these components.

Resilience is defined as the ecosystem's ability to withstand and absorb the fire impacts, which includes recovery time and copping capacity.

2.5.2 Overview and description of relevant models

The significance of the wildfire risk content and the importance during firefighting planning has led to a significant number of research works, aiming at the protection of humans and ecosystems from the specific natural disaster. For each of the described methods, a series of quality criteria had to be fulfilled so as to be selected for further analysis. Those criteria are:

- a close relevance with the wildfire onset and spread probability estimation,
- a clear reference to the three main dimensions of wildfire risk (hazard, exposure, and vulnerability),
- a robust method to assess and to distribute wildfire risk preferably on a spatial basis,
- a wide range of applicability covering different types of ecosystems including Wildland – Urban Interface (WUI) areas,
- a highlighted evaluation part against data that were not used during model's calibration,
- an inherent simplicity to endorse their operational value.

The wildfire risk assessment can be based on fire zoning determination of long term variables (structural indices), on short term variables (dynamic indices) or a combination of both. Overall, the process of developing a wildfire risk model includes the following critical steps:

- Data collection of burned areas on a spatial basis. The obtained dichotomous data can be used for estimating the probability of wildfire occurrence based on a number of explanatory variables, or for verifying the estimated wildfire risk through spatial validation processes.
- Distribution of explanatory variables (vegetation, fuel, weather, human presence, topography) on a spatial basis. Remote sensing applications are also essential in this step, in terms of mapping accuracy.
- Application of selected model(s). The most important methods/tools for this procedure are:
- Fixed-parameter wildfire risk model (Chuvieco and Congalton 1989, Jaiswal et al. 2002, Dong et al. 2005, Adab et al. 2013).
- Multicriteria analysis – The Analytical Hierarchy Process (AHP) (Setiawan et al. 2004, Yin et al. 2004, Eugenio et al. 2016, Pourghasemi et al. 2016, Suryabhagavan et al. 2016).
- Artificial Neural Networks (ANN) and Random Forests analysis (Jaafari and Pourghasemi 2019).
- Fire simulators and GIS analysis (Mitsopoulos et al. 2015**,** Kanga et al. 2016).
- The logistic regression and generalized least squares models (Mohammadi et al. 2013, Kwak et al. 2012).
- Hot spot analysis (Feltman et al. 2012).
- Maxtend model – Maximum entropy theory (Yang et al. 2021).
- Forest fire weather models (Van Wagner and Pickett 1985, Cohen and Deeming 1985, Sirca et al. 2018).
- Composite models (Kaloudis et al. 2005).
- Validation of the model's predictive power, by using data that have not been utilized during model's development stage. For this purpose, the hold-out method has been widely used along with a ROC (receiver operating characteristic) analysis.
- Implementation of the final model using a GIS platform.

In the following, the most complete methods/indices, in terms of integration of various components of fire risk as well as their acceptance of the scientific community, are briefly described.

M23.1 In the frame of the specific study, a fixed-parameter model is utilized for wildfire zone risk mapping in Madhya Pradesh, India. The introduced model was based on Remote Sensing Satellite images and GIS for vegetation mapping, in an effort to generate indexed maps of Wildfire Risk distribution.

M23.2 In the current research, a spatially weighted index model was implemented to estimate forest fire hazard in Malaysia, by integrating GIS-based and multi-criteria analysis (Analytical Hierarchy Process) to provide valuable information about areas most likely to be affected by fire.

M23.3 Forest fire risk zones were recognized by assigning subjective weights to the classes of all the coverage layers according to their sensitivity to fire in China, using a GIS software. The results were found to be highly compatible with actual fire-affected sites.

M23.4 A method for integrating remote sensing and GIS was developed and applied to long-term forest fire risk zone mapping along with a fixed-parameter model and variable assigned weights. The method can be used for forest management purposes, and it can be applied to various types of ecosystems.

M23.5 A Structural Fire Index, a Fire Risk Index, and a new index called the Hybrid Fire Index were used to delineate fire risk in northeastern Iran that is subjected to frequent forest fires. In addition, hot spot data derived from the MODIS satellite sensor were used to validate the indices, along with receiver operating characteristic (ROC) curves. The Hybrid Fire Index was superior to the other two indices.

M23.6 The basic aim of the study was to develop a statistical model for distributing a forest fire risk map in Southeastern Brazil, using GIS and weights assignment to nine variables divided into physical and climatic factors. The predictive power of the model was compared with historic heat spot recordings.

M23.7 A proportion of FARSITE simulation runs that burned a particular point was accumulated over the entire study area in India and the identification of potential active spots of fire risk was estimated in the second phase. According to the authors, simulation modeling constitutes an adequate tool to estimate risk when actual risk data are limited or unavailable.

M23.8 A modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic (MFL) models were integrated in a geographic information system (GIS) environment in order to assess forest fire susceptibility maps (FFSMs) and their performances comparison. The validation procedure was based on the receiver operating characteristic (ROC) curve along with the forest fire locations that were not used during the model building process.

M23.9 A multi-criteria decision-making process along with GIS and remote sensing techniques were adopted to derive fire susceptibility map of an area that was located in southwestern Ethiopia. According to the authors, the identification of locations of fire-prone areas a priori can be used effectively to plan fire control measures.

M23.10 The basic aim of the study was to assess spatial wildfire risk in a typical Mediterranean wildland–urban interface (WUI) in Greece and the potential effect of three different conditions of the fire environment. The study was based on simulations using the FlamMap and ArcFuels tools to characterize the potential response of the wildfire risk to a range of different burning scenarios.

M23.11 A geospatial (or geographical information system) analysis approach was implemented to identify socioeconomic variables that contribute to wildfire occurrence, in in South Carolina, US. The research was based on hot spot analysis, as the primary research tool using socio-economic data.

M23.12 A generalized linear model (GLM) with Poisson distribution was used to test the influence of fixed effects on the occurrence of forest fires, based on GIS-derived explanatory variables. Second, the site-specific characteristics of forest fires were analyzed by spatial regression analysis using a generalized linear mixed model (GLMM), which can consider for spatial autocorrelation. The fitted models were validated and compared using the multiple correlation and root mean square error (RMSE).

M23.13 Logistic regression was used to analyze the forest fire risk and identify the most influential factors for forest fires occurrence. Climatic variables, human factors and physiography were considered and their correlation with the occurrence of fires was investigated. The results of the model validation and sensitivity of various areas to fire were examined with the receiver operating characteristic (ROC) curve and the Hosmer–Lemeshow test.

M23.14 The effect of different landscape characteristics on wildfire occurrence and its spatial distribution over a fire-prone landscape in the Zagros Mountains, Iran was investigated. To this end, a random forests (RFs) model was utilized to link historical fire events to a set of wildfire causative factors in order to measure the importance of each factor on fire ignition. Furthermore, a data-mining model was implemented to produce an accurate estimate of wildfire probability across the study area. Finally, the receiver operating characteristic (ROC) - AUC method was used for the assessment and validation of the results.

M23.15 Twelve factors in total related to topography, climatic conditions, vegetation attributes, and human activities were used as environmental variables affecting wildfire occurrence in Hunan Province, China. Then, a Maxent (Maximum entropy) wildfire risk assessment model was implemented with GIS, which analyzed the contribution, importance, and response of environmental variables to wildfire.

M23.16 Digitally processed Thematic Mapper data were integrated with other layers of geographic information system to derive a forest fire hazard map. The research area was located in the Mediterranean coast of Spain. A linear model was implemented to integrate the spatial data layers in a single fire hazard index, along with empirical weights. The proposed model performed properly in identifying the areas subjected to a higher fire hazard.

M23.17 The Canadian Forest Fire Danger Rating System, is a comprehensive system of tools to evaluate environmental factors that influence the ignition, spread, and behavior of a potential wildland fire. It provides a general estimation of fire danger in forested and rural areas. The two main parts of the CFFDRS

System is the Fire Weather Index (FWI) system to anticipate the potential for daily fire ignition across the landscape, and the Canadian Forest Fire Behavior Prediction (FBP) System to assess potential fire behavior.

M23.18 The National Fire-Danger Rating System (NFDRS) is a tool for the estimation of the fire danger for a given area, by providing indexes for measuring fire potential in wildlands. It combines the effects of existing and expected levels of selected fire danger factors into one or more qualitative or numeric indices that reflect an area's fire protection needs.

M23.19 A set of statistical tools, such as Spearman rank correlation, Index Value Distribution and Percentile Analysis, and Logistic Regression were applied to evaluate the performance of each Fire Danger index by comparing Fire Danger values with fire occurrence indicators, in a fire-prone Mediterranean area in Sardinia Island, Italy. According to the authors, two of the tested Fire Danger indexes reached a good overall performance.

M23.20 In the current study, a composite index is proposed for fire destruction danger assessment. Wildfire incidence and fire severity (FS), in association with the values in threat and the sensitivity of these values to fire, are some of its constituent parameters. The index is computed by use of logic programming within a multi-criteria Decision Support System (DSS) in a Mediterranean area in Greece.

Overall, all methods are characterized by inherent simplifications, applicability constrains and different levels of prediction accuracy. Hence, an assessment is required in order to select the most suitable model for wildfire ignition modelling.

Table 8: Overview of models for wildfire risk assessment and their variables.

Long-term variables / Structural indices			Method	Variables
Reference	**Model**	**Wildfire component**		
Jaiswal et al. (2002)	**23.1**	Forest fire risk zone	**Fire risk = 10Vegetation variable+2Proximity human habitation+2Road factor+3Slope factor**	Vegetation type, slope, proximity to settlements, distance from roads
Setiawan et al. (2004)	**23.2**	Fire hazard	Multi-criteria analysis (**MCA**) – Analytical hierarchy process (**AHP**) $H = 0.432V+0.289PR+0.135A+0.108S+0.045E$ Where **H** is fire hazard.	**V** = vegetation, **PR** = proximity to roads, **A** = aspect, **S** = slope, **E** = elevation
Yin et al. (2004)	**23.3**	Forest fire risk	Analytic hierarchy process (AHP) **Forest fire risk = 0.40Vegetation+0.15Proximity to settlements+0.15Slope+0.15Aspect+0.15Altitude**	Vegetation, proximity to settlements, slope, aspect, altitude
Dong et al. (2005)	**23.4**	Forest fire risk	**Forest fire risk = 7Vegetation Type+ 5(Slope + Aspect + Elevation) + 3(Distance from roads + Distance from settlements +Distance from farmlands)**	Vegetation type, slope, aspect, altitude and distance from roads, farmlands and settlement
Adab et al. (2013)	**23.5**	Fire risk	Structural Fire Index (SFI) $SFI=1+100v+30s+10a+5r+2e$ Fire Risk Index (FRI) $FRI=7V_i+5(S+A)+3(D_r+D_s)$ Hybrid Fire Index (HFI) $HFI=(100_v+50_s+25_a+10(r+c)+5_e)/10$	**v**=vegetation moisture, **s**=slope, **a**=aspect, **D**$_r$, **r**=distance from roads, e=elevation **D**$_s$, **c**=vicinity to settlements

Eugenio et al. (2016)	**23.6**	Forest fire risk	Weighted hierarchical analysis (Analytical Hierarchy Process – AHP) **IR=(0.3070Prec+0.2182Temp+0.1543Def+0.1089Slo+0.0764Road+0.0533Use+0.0370Pet+0.0259Asp+0.0189Dem)**	**IR**=Fire risk **DEM**=digital elevation model **ASP**=reclassified terrain orientation **PET**=reclassified potential evapotranspiration **USE**=reclassified land use **ROAD**=reclassified Euclidean distance of the roads **SLO**=reclassified slope **DEF**=reclassified water deficit **TEMP**=reclassified temperature **PREC**=reclassified precipitation
Kanga et al. (2016)	**23.7**	Forest fire risk	GIS (Geographic Information System) and Fire simulation (FARSITE)	Topographic, vegetation and climate datasets
Pourghasemi et al. (2016)	**23.8**	Forest fire susceptibility	Analytical hierarchy process (M-AHP) and Mamdani fuzzy logic (MFL)	Altitude, slope aspect, slope angle, annual temperature, wind effect, land use, and normalized different vegetation index
Suryabhagavan et al. (2016)	**23.9**	Identification of fire-prone areas	Multi-criteria decision-making technique (AHP) **Forest Fire Susceptibility = (Vegetation type) × 0.3854 + (Slope) × 0.2531 + (Aspect) × 0.1626 + (Elevation) × 0.0983 +(Settlement) × 0.0627 + (Road) × 0.0380**.	Elevation, slope, aspect, vegetation type, proximity to settlements, distance from roads
Mitsopoulos et al. (2015)	**23.10**	Wildfire risk	GIS (Geographic Information System) and Fire simulation (Flammap and ArcFuels ver.10)	Fuel models
Feltman et al. (2012)	**23.11**	Wildfire occurrence and intensity	Hot spot analysis	Socioeconomic factors: Low population densities, low levels of population change, high poverty rate, low educational attainment level, and low road density
Kwak et al. (2012)	**23.12**	Forest fire occurrence	Generalized linear model (GLM) with Poisson distribution and generalized linear mixed model (GLMM)	Slope, elevation, aspect, population density, distance from road, and forest cover
Mohammadi et al. (2013)	**23.13**	Forest fire risk	Logistic regression $P_i = \frac{\exp(\beta_0 + \beta_{1X1i} + \beta_{2X2i} + \dots +}{1 + \exp(\beta_0 + \beta_{1X1i} + \beta_{2X2i} + \dots}$	Climatic variables (temperature and annual precipitation), human factors (distance from streams and farmland) and physiography (land slope and elevation)
Jaafari and Pourghasemi (2019)	**23.14**	Wildfire probability	Random Forest Model – Support Vector Machine Model	Slope degree, aspect, altitude, mean annual temperature and rainfall, wind effect, and proximity to settlements, rivers, and roads
Yang et al. (2021)	**23.15**	Wildfire occurrence	Maxtend model – Maximum entropy theory $H(x) = -\sum_{(i)}^{\pi} p(x = x_i) \log p(x = x_i) = -\sum_{(i)}^{\pi} p(X) \log p(X)$	Topography, climatic conditions, vegetation attributes, and human activities

			X is the wildfire to be predicted, H(x) is the information entropy of X. The spatial distribution of wildfire X is influenced by the environmental variable Y. $H\,(X\|Y\|) \;=\; \sum_{i}^{\pi} p(X,\,Y)\log p\,(X,\,Y)$ The Maxent model X*=argmaxH(X|Y)	
Chuvieco and Congalton (1989)	**23.16**	Forest fire hazard	**Hazard=1+100v+30s+10a+5r+2e**	Explanatory variables v=vegetation s=slope a=aspect r=roads e=elevation
Short term variables / Dynamic indices				
Reference	**Model**	**Wildfire component**	**Method**	**Variables**
Van Wagner and Pickett (1985)	**23.17**	Forest Fire Weather Index Canadian Forest Fire Danger Rating System (**CFFDRS**)	Fine Fuel Moisture Code (FFMC) $m_0 \;=\; \frac{147.2(101\,-\,F_0)}{(59.5\,+\,F_0)}\;[eq.1]$ $r_f \;=\; r_0\,-\,0.5,\, r_0\,>\,0.5\;[eq.2]$ $m_r = m_0 + 42.5r_f\left(e^{-100(251-m_0)}\right)\left(1 - e^{-\frac{6.93}{r}}\right),\, m_0\,\leq\,150\;[eq.3a]$ $m_r = m_0 + 42.5r_f\left(e^{-100(251-m_0)}\right)\left(1-e^{-\frac{6.93}{r_f}}\right) + 0.0015(m_0\,-\,150)^2 r_f^{0.5},\, m_0 > 150\;[eq.3b]$ $E_d \;=\; 0.942H^{0.679}\,+\,11e^{\frac{(H-100)}{10}} + 0.18(21.1\,-\,T)(1 - e^{-0.115H})\;[eq.4]$ $E_w \;=\; 0.618H^{0.753}\,+\,11e^{\frac{(H-100)}{10}} + 0.18(21.1\,-\,T)(1 - e^{-0.115H})\;[eq.5]$	**Weather** -noon temperature, °C -noon relative humidity, % -noon wind speed, km/h **r_o** -rainfall in open, measured once daily at noon, mm -effective rainfall, FFMC -effective rainfall, DMC -effective rainfall, DC **Fine Fuel Moisture Code (FFMC)** **m_o** -fine fuel moisture content from previous day -fine fuel moisture content after rain -fine fuel moisture content after drying -fine fuel EMC for drying -fine fuel EMC for wetting -intermediate step in calculation of k_d -log drying rate, FFMC, $\log_{10}$m/day -intermediate step in

			$k_0 = 0.424\left[1 - \left(\frac{H}{100}\right)^{1.7}\right] + 0.0694W^{0.5}\left[1 - \left(\frac{H}{100}\right)^{8}\right] [eq.6a]$ $k_d = k_0 0.581e^{0.0365T} [eq.6b]$ $k_l = 0.424\left[1 - \left(\frac{100-H}{100}\right)^{1.7}\right] + 0.0694W^{0.5}\left[1 - \left(\frac{100-H}{100}\right)^{8}\right] [eq.7a]$ $k_w = k_1 0.581e^{0.0365T} [eq.7b]$ $m = E_d + (m_0 - E_d)10^{-k_d} [eq.8]$ $m = E_w - (E_w - m_0)10^{-k_w} [eq.9]$ $F = \frac{59.5(250 - m)}{147.2 + m} [eq.10]$ Restrictions: 1) Equation 3 (a or b) must not be used when $r_o \leq 0.5$ mm; that is, in dry weather the rainfall routine must be omitted 2) m has an upper limit of 250; that is, when Equation 3 (a or b) yields $m_r > 250$, let $m_r = 250$. Duff Moisture Code (DMC) $r_e = 0.92r_0 - 1.27,\ r_0 > 1.5 [eq.11]$ $M_0 = 20 + e^{\frac{(5.6348 - P_0)}{43.43}} [eq.12]$ $b = \frac{100}{(0.5 + 0.3P_o)},\ P_{0 \leq 33\ [eq.13a]}$ $b = 14 - 1.3\ln P_0,\ 33 < P_0 \leq 65 [eq.13b]$ $b = 6.2\ln P_0 - 17.2,\ P_0 > 65 [eq.13c]$ $M_r = M_0 + \frac{1000r_e}{48.77 + br_e} [eq.14]$ $P_r = 244.72 - 43.43\ln(M_r - 20)\ [eq.20]$ $K = 1.894(T + 1.1)(100 - H)L_e 10^{-6} [eq.16]$ $P = P_0(or\ P_r) + 100K [eq.17]$ Restrictions: 1) Equations 11 to 15 are not used unless $r_o > 1.5$; that is, the rainfall	calculation of k_w -log wetting rate, $\log_{10}$m/day -previous day's FFMC -FFMC **Duff Moisture Code (DMC)** **M_o** - duff moisture content from previous day - duff moisture content after rain - duff moisture content after drying - log drying rate in DMC, $\log_{10}$M/day - effective day length in DMC, hours - slope variable in DMC rain Effect - previous day's DMC - DMC after rain - DMC **Drought Code (DC)** **Q** - moisture equivalent of DC, units of 0.254 mm **Q_o** - moisture equivalent of previous day's DC **Q_r** - moisture equivalent after rain - potential evapotranspiration, units of 0.254 mm water/day - day length adjustment in DC **Fire Behavior Indexes (ISI, BUI, FWI)** **f(W)** - wind function **f(F)** - fine fuel moisture function **R** - Initial Spread Index (ISI) **U** - Buildup Index (BUI) **B** - FWI (intermediate form) - FWI (final form) Severity Rating

			routine must be omitted in dry weather 2) P_r cannot theoretically be less than zero. Negative values must be raised to zero 3) Values of T less than – 1.1 must not be used in Eq.16. If T<-1.1, let T=-1.1. Drought Code (DC) $r_d = 0.83r_0 - 1.27,\ r > 2.8\ [eq.18]$ $Q_0 = 800e^{\{-\frac{D_0}{400}}\ [eq.19]$ $Q_r = Q_0 + 3.937r_d\ [eq.20]$ $D_r = 400\ln\left(\frac{800}{Q_r}\right)\ [eq.21]$ $V = 0.36(T + 2.8) + L_f [eq.22]$ $D = D_0(or\ D_r) + 0.5V\ [eq.23]$ Restrictions: 1) Equations 18 to 21 are not used unless r_o>2.8; that is, in dry weather the rainfall routine must be omitted 2) D, cannot theoretically be less than zero. Negative values must be raised to zero 3) Values of T less than -2.8 must not be used in Equation 22. If T<-2.8, let T=-2.8 4) V cannot be negative. If Equation 22 produces a negative result, let V=O. Initial Spread Index (ISI) $f(W) = e^{0.05039W}\ [eq.24]$ $f(F) = 91.9e^{-0.1386m}\left[1 + \frac{m^{5.31}}{4.93 \cdot 10^7}\right]\ [eq.25]$ $R = 0.208f(w)f(F)\ [eq.26]$ Buildup Index (BUI) $U = 0.8PD(P + 0.4D),\ P \leq 0.4D\ [eq.27a]$ $U = P - \left[1 - \frac{0.8D}{(P + 0.4D)}\right](0.92 + (0.0114P)^{1.7}),\ P > 0.4D\ [eq.27b]$ Fire Weather Index (FWI)	**DSR** - Daily Severity Rating

			$f(D) = 0.626U^{0.809} + 2, U, = 80\ [eq. 28a]$ $f(D) = \frac{1000}{25 + 108.64e^{-0.023U}}, U > 80\ [eq. 28b]$ $B = 0.1R_f(D)\ [eq. 29]$ $\ln S = 2.72(0.434 \ln B)^{0.647}, B > 1\ [eq. 30a]$ $S = B, B \leq 1\ [eq. 30b]$ Daily Severity Rating (DSR) $DSR = 0.0272(FWI)^{1.77}\ [eq. 31]$	
Cohen and Deeming 1985	**23.18**	Wildfire occurrence potential National Fire-Danger Rating System (NFDRS)	Spread Component SC=IRND(ROS) ROS=IR·ZETA·(1.0+PHISLP+PHIWND)/HTSINK (ft/min) Energy Release Component ERC=IRND(0.04·IRE·TAU) Burning Index $BI = IRND(3.01(SC \cdot ERC)^{0.46})$ Ignition Component IC=IRND(0.10·P(I)·P(F/I)) Fire Load Index $FLI = 0.71\sqrt{(BI^2 + (LOI + MCOI)^2)}$ Keetch-Bryam Drought Index When Δ_t is equal to one day $KBDI = Q + \frac{(800 - Q)(0.968e^{0.0486T} - 8.3)\Delta_t}{1 + 10.88r^{-0.0441P}}$ The final equation in SI units: $KBDI = Q + \frac{(203.2 - Q)\left(0.968e^{(0.0875T+1.5552)}\right.}{1 + 10.88e^{-0.001736P}}$	**SC=**NFDRS spread component **IRND=**Round-off function of **ROS=**Forward rate of spread of flaming front (ft/min) **IR=**Surface area weighted reaction intensity **ZETA=**No-wind propagating flux ratio **PHISLP=**Multiplier for slope effect **PHIWND=**Multiplier for wind effect **HTSINK=**Heat sink term **ERC=**NFDRS energy release component **IRE=**Loading weighted reaction intensity **TAU=**Calculated residence time of flaming front (min). **P(F/I)=** Probability that ignition will result in a reportable fire **P(I)=**Probability that a firebrand will produce a successful fire start in dead, fine fuels **LOI=**Lighting –caused fire occurrence index **MCOI=**NFDRS human-caused index of fire occurrence **Q=**is the previous' day *KBDI* minus net rainfall **T=**Air temperature **Δ_t=**Time increment **P=**Rainfall
Sirca et al. 2018	**23.19**	**Integrated Fire Index (IFI)**	IFI=DC+MC+R+FC	**Rg =** The global daily radiation (W/m^2) **T =** The mean daily temperature (^{o}C)

			Where, ***DC*** is the drought code: $DC = \frac{e^{\left(\frac{0.261RgT}{\lambda}\right)}}{1+\sqrt{(P_a)+\sqrt[3]{P_{c100}}}}$ ***MC*** accounts for the meteorological conditions: $MC = 0.14[e^{0.0625T_x} + e^{0.1WS} + e^{-0.062RH_n}]$ ***R*** corresponds to the maximum daily solar radiation ***RSx.*** If RSx<400 (W/m2), then R=0.24 If 400≤RSx≤800 (W/m2), then R=0.32 If RSx>800 (W/m2), then R=0.1 ***FC*** is related to fuel characteristics: FC=LAI·LAD·DW The calculation of the FC requires the definition of specific fuel categories	**λ =** The latent heat of evaporation **Pa** = daily rainfall (mm) **P_{c100}** = the rainfall of the last 4 days (mm) **Tx** = The maximum daily air temperature (°C) **WS =** The maximum daily wind speed (km/h) **RHn =** The minimum daily air temperature (°C) **LAI =** Leaf Area Index (dimensionless) **LAD =** The Leaf Area **DW** = Fuel moisture content
Composite indices				
Reference	**Num**	**Wildfire component**	**Method**	**Variables**
Kaloudis et al. (2005)	**23.20**	Wild Fire Destruction Danger Index (WFDDI)	Logic Programming incorporating logic rules through Fuzzy Relational Inference Language (FRIL) environment and fuzzy logic: (property of_X is f) if (feature_1 of_X is f1) and (feature_2 of_X is f2) and . (feature_n of_X is fn) where keywords are denoted in bold. The statement *(property **is** f)* is the conclusion or head of the rule. Each *(feature_i **is** f_i)* is a condition, where f_i is a value assigned to feature *i*. The logical conjunction of all the conditions is the body of the rule. The interpretation of the rule is that if all the conditions are satisfied then the conclusion is true. The set of all the rules, which model the domain knowledge, constitutes the knowledge base. A value after a keyword ***is*** was replaced by a fuzzy set. Furthermore, each condition of the rule was associated with a weight and the conclusion of the rule	**FIP** -Fire Incidence History -Population Change Rate -Income per Capita Change Rate **VT** -Price -Utility **VFS** -Flammability -Destruction degree

			was a weighted combination of its conditions. The sum of weights *(w)* was equal to 1. During the evaluation of the rule, a site's characteristic was matched against the relevant rule, thus giving a partial probability interval, support pair (α_i,β_i). In this way, the rule body (set of conditions) was assigned a probability interval, computed from the formula $[\alpha, \beta] = \left[S\left(\sum_{i=1}^{n} W_i\, a_i\right), S\left(\sum_{i=1}^{n} W_i\, \beta_i\right)\right]$ Where S is a function, S:[0,1]→[0,1]. The degree of rule satisfaction was indicated by a final interval (support pair *(γ_1, γ_2)*, containing the probability to be true, that was estimated by $\gamma_1 = \{n_1\beta + p_1(1-\beta)\ if\ n_1 \leq p_1 n_1\alpha + p_1(1-a),\ if\ n_1 > p_1\}$ And $\gamma_2 = \{n_2\beta + p_2(1-a)\ if\ n_2 \leq p_2 n_2\alpha + p_2(1-\beta),\ if\ n_2 > p_2\}$ The **Fire Risk** was based on the following components: Fire incidence probability (FIP) Fire Severity (FS) Fire Severity Probability (FSP) Values in Threat (VT) Values Fire Sensitivity (VFS)	

2.5.3 Assessment of relevant models and tools

An evaluation for the majority of the models relevant to fire risk assessment is provided in appendix 5.4 (Table 49), whereas an evaluation of the corresponding software tools that implement (calculate) the models is provided in Table 50 of the same chapter.

2.6 M24: Models of surface fuel load

2.6.1 Most widely used model for the spread rate of surface fire

Three general types of wildland fire are currently recognized, depending on the fuel type that it is actually involved in the combustion process: the ground fires, the surface, and the crown fires.

A surface fire is the type of fire that consumes the surface fuels, between the ground fuels and the canopy, defined as aerial fuels (Scott and Reinhardt 2001). Surface fuels consist of needles, leaves, grass, dead and down branch wood and logs, shrubs, low brush, and short trees (Brown et al. 1982). From the operational point of view, surface fire behavior is a key factor during wildfire modeling. Ground fires are burning slowly due to oxygen limitations below the surface layer, and they are difficult to contain, but their occurrence is rather rare. Crown fires consist of the most erratic type of wildland fire, releasing large amounts of energy at the flaming front and they are particularly difficult to mitigate by both the ground and the air fighting forces. However, they are closely linked with a surface fire, supplying the required energy for the ongoing crowning phase through the ladder fuels.

Surface fires are by far the most common wildfire type, and they can be characterized by increased spread rates in case of unsheltered fuel exposure to wind activity and steep terrain. One of the most important fire attributes at the flaming front is the spread rate (*Ros*) which is usually estimated in meters per minute (*m/min*). It is closely connected with the flame length (*FL)* in meters, and the fireline intensity (*I)* in kW/m (Byram 1959), a measure of the released energy rate at the flaming front. From a fire management perspective, it is very important to predict the rate of spread of a potential wildfire, since it currently expresses the overall fire severity. In this sense, a number of significant models have been suggested in the world literature for the prediction of the spread rate of a flaming front. The **most widely used model** has been proposed by Rothermel (1972), and it has been included to the BehavePlus (Andrews 1986), the NEXUS (Scott 1999), the FARSITE (Finney 2004), and the FlamMap (Finney 2006) fire modeling systems.

It is actually a **semi-empirical** model based on a Frandsen's (1971) heat balance model, data from wind tunnel experiments in various types of artificial fuel beds (Rothermel and Anderson 1966) and from field experiments of grassfires in Australia (McArthur 1969). The Rothermels' basic fire spread model (Rothermel 1972) as it was adapted by Albini 1976 is expressed through the following equation (Andrews 2018):

$$R_{os} = \frac{1_R \xi (1 + \varphi_w + \varphi_s)}{\rho_b \varepsilon Q_{ig}}$$

where:

Ros is the rate of spread of the flaming front estimated in m/min,

I_R is the reaction intensity, or the released energy of the fire front per unit area (kW/m^2/min),

ξ is the propagating flux ratio expressing the proportion of the reaction intensity that contributes to forward fire spread by heating fuel ahead of the flaming front,

φ_w is the function of mid-flame wind speed in increasing the propagation flux ratio, dimensionless,

φ_s is the function of slope steepness in increasing the propagation flux ratio, dimensionless,

ρ_b is the fuelbed bulk density in kg/m^3,

ε is the effective heating number or the fraction of the total fuel load that is heated to ignition by the time of flaming combustion,

Q_{ig} is the amount of heat required to heat one pound of fuel to its ignition temperature.

Operational inputs

The model was designed to use a series of input variables from the fire environment before the fire behavior simulation. The inputs are basically grouped in the following two main categories, which are described in detail in the sub-sections that follow:

- Fuel properties
- Environmental values

2.6.2 *Fuel properties*

Fuel properties include the following:

- **Fuel model type:** *Static (S)* or *Dynamic (D)*. The fuel models containing a live herbaceous component can be classified as *Dynamic* type. In this case, a portion of the live herbaceous fuel load is transferred into the 1-hour time-lag dead herbaceous load depending upon the live herbaceous fuel moisture content. When the moisture content is larger than 120%, the total amount of herbaceous fuel load remains in the current fuel class, whereas when the moisture is less than 30% the total herbaceous fuel load is transferred to the 1-hour fuel class.
- **Dead fuel components by dry weight:** They are grouped in time-lag classes (1-hour, 10-hour, 100-hour and 1000-h), corresponding to the time it would take for 2/3 of the dead fuel to respond to changes of atmospheric moisture. The thinner fuels respond more rapidly to changes in the environmental conditions. According to the metric system, they are expressed in tons per hectare (t/ha). The time-lag classes are corresponding to the following dimensions (diameter) of the dead fuels:
- The **1-hour** time-lag fuels (0 to 6.4 mm in diameter), including needles, leaves, dead herbaceous plants and fine (dead) plant parts.
- The **10-hour** time-lag fuels (0.6 to 2.5 cm in diameter), including dead medium plant parts.
- The **100-hour** time-lag fuels (2.5 to 7.6 cm in diameter), composed by the largest dead plant parts.
- The **1000-hour** time-lag fuels (7.6 to 20.32 cm in diameter)
- **Live herbaceous fuel load:** It expresses the oven-dry weight in tons per hectare (t/ha) of the living annual or perennial non-woody plants, including grasses and forbs.
- **Live woody fuel load:** It represents the oven-dry weight in tons per hectare (t/ha) of live woody fuel particles. They consist of fine twigs (less than 0.64 cm diameter), live shrub and tree leaves of small dimensions.
- **1-hour fuel Surface Area - to - Volume ratio (SAV)**: It expresses the amount of the fuels' surface area, divided by the volume of the specific fuel in m^2/m^3. Fuels with higher SAV values are characterized by increased moisture loss rates, which would decrease ignition time, leading to increased spread rate. The fuel class corresponds to 1-hour time lag dead fuels, between 0 to 6.4 mm in diameter. It ranges between 358 and 13,123 m^2/m^3.
- **Live herbaceous fuel Surface Area - to - Volume ratio (SAV):** It is estimated by dividing the total surface area of herbaceous plants by the total volume of the leaves. It is expressed in m^2/m^3 ranging between 4,921 and 11,483 m^2/m^3.
- **Live woody fuel Surface Area - to - Volume ratio (SAV):** It is the result of dividing the total surface area of woody plant composed by leaves, by the volume occupied by the plant leaves, in m^2/m^3. Usually, it ranges between 3,281 and 6,562 m^2/m^3.
- **Fuel bed depth:** It reflects a particular effect on wildfire behavior by regulating the surface fuel bulk density (total fuel load divided by fuel bed depth), and the packing ratio (as the bulk density divided by the total particle density). However, fuel bed depth is particularly difficult to be accurately estimated in field conditions and several modelling methods are usually applied. It is currently expressed in cm or m. The Rothermel's surface fire model is sensitive to the specific fuel attribute and significant effort must be put for its estimation.
- **Dead fuel moisture of extinction:** It is defined as the weighted average dead fuel moisture content (%) at which the fuel will not sustain a spreading fire at the surface layer. It is rather a user-assigned value, between 5 and 100%.
- **Dead fuel heat content:** This variable represents the amount of heat energy that is included in a unit of dead fuels. In general terms, higher heat content levels leads to increased reaction intensity and consequently higher spread rates. It is expressed in kJ/kg, within a range between 13,967 and 27,934 kJ/kg.

- **Live fuel heat content:** It expresses the amount of heat energy that is included in a unit of live fuels, in kJ/kg. The live heat content is referred to both, herbaceous and woody live fuels. Similar to the dead fuel heat content, it ranges between 13,967 and 27,934 kJ/kg.
- **Dead fuel moisture:** It is defined as the percentage (%) of the dead fuel weight that is composed by water, calculated on an oven-dry weight basis. It is estimated through the following equation:

$$FMC = \frac{Weight_{wet} - Weight_{dry}}{Weight_{dry}}$$

It is an important variable affecting surface fire behavior. Dead fuel moisture may vary within the same day or between days, whereas live fuel moisture may vary weekly on a seasonal basis.

- The **1-hour** time-lag fuel (0 to 6.4 mm in diameter) moisture, with a great impact on surface fire behavior. It ranges from 1 to 60%.
- The **10-hour** time-lag fuel (0.6 to 2.5 cm in diameter) moisture content. The moisture of the specific fuel class has less impact on surface fire spread than the moisture of the 1-hour time-lag fuel. It also ranges from 1 to 60%.
- The **100-hour** time-lag fuel (2.5 to 7.6 cm in diameter) moisture content. It has the lowest impact on surface fire spread rate compared with the moisture of the previous fuel classes. The minimum input value for this variable is 1% and the maximum 60%.

Due to the large variability of the dead fuel moisture during the day and/or between days, two main approaches are used in order to estimate dead fuel moisture values. The first method is to use the fixed values provided by Rothermel (1991) according to Table 9.

Table 9: Moisture content values (%) by fuel class for five seasonal conditions.

	Seasonal moisture condition				
Fuel Class	**Early spring before greenup**	**Late spring after greenup**	**Normal summer**	**Drought summer**	**Late summer severe drought**
1-h	8	9	6	4	3
10-h	14	11	8	5	4
100-h	18	15	10	7	6
live	65	195	117	78	70

The second method includes a simplification of Rothermel’s (1983) daytime tables for the estimation of the fine fuel moisture content (1-hour and 10-hour time-lag fuel). The moisture of the other class can be calculated empirically by adding 2 units to the 10-h fuel. The model has been incorporated into the BehavePlus as an additive tool, using the following parameters:

- The dry bulb temperature (between 10 and 129 °F)
- The relative humidity (between 0 – 100%)
- The month of the year
- The time of day (between 08:00 and sunset)
- The elevation difference between the projection point and the reference site
- The slope percentage (from 0 to 30% and >30%)
- The aspect of the reference site
- The fuel shading (below or above 50%)
- **Live herbaceous fuel moisture:** It is defined as the percentage (%) of the live grasses or forbs fuel weight that is composed by water, calculated on an oven-dry weight basis. Since it can be directly connected with the 1-hour dead fuels under the *Dynamic* condition, it can affect surface spread rate to a large extent. The threshold values are between 30 and 300%.

- **Live woody fuel moisture:** It is defined as the percentage (%) of the live shrub foliage and very fine stems or forbs fuel weight that is composed by water, calculated on an oven-dry weight basis. Table 10 has been incorporated in the BehavePlus fire modeling system for the estimation of the live woody fuel moisture, when no other information is available.

Table 10: Guidelines for the estimation of the live woody fuel moisture.

Moisture (%)	Stage of vegetative development
300	Fresh foliage, annuals developing, early in growing cycle
200	Maturing foliage, still developing with full turgor
100	Mature foliage, new growth complete and comparable to older perennial foliage
50	Entering dormancy, coloration starting, some leaves may have dropped from the stem
30	Completely cured, treat as dead fuel

The same table (Table 10) can be used for the estimation of the live herbaceous fuel moisture when no other information is available.

2.6.3 Environmental values

Environmental values include:

- **Midflame wind speed (upslope):** According to Albini and Baughman (1979) midflame wind speed is defined as the average wind speed values measured from the top of the fuel bed to the top of the flame structure above the fuel. The eye-level wind speed (1.5 meters) is usually used instead of midflame when estimating wind speed in field conditions. It is expressed in km/h, between 0 and 64.4 km/h.
- **Slope steepness:** It reflects the maximum steepness of the slope where a potential fire is spreading. It can be calculated by dividing the slope elevation change by slope horizontal distance. It is expressed either with percentage (%) or by degrees (°). The threshold values are between 0 and 604%.

The Rorthermel (1972) surface spread model has been successfully implemented in the *R* programming language by Vacchiano and Ascoli (2015), through the “Rothermel” R package and the ros () function. According to the authors, it is actually a new tool for complex analyses using the Rothermel surface fire model.

In order to be able to calculate surface fire characteristics through the above-mentioned models a systematic and detailed inventory of fuel characteristics is needed per fuel type and location vegetation grow conditions, such as grass, bushes, or forest understory vegetation. For this reason, in Table 11, the parameters of surface fuel models needed for the calculation of surface fires characteristics are given. In Table 12, a more detailed presentation of surface fuel parameter is given.

Table 11: Basic inputs for surface fire spread rate modelling.

<table>
<tr><th colspan="5">BehavePlus, NEXUS, FARSITE, FlamMap</th></tr>
<tr><th>Code</th><th>Description</th><th>Type</th><th>Values Range</th><th>Units</th></tr>
<tr><td>FMID</td><td>Fuel model code</td><td>Integer (2)</td><td>1 - 99</td><td>-</td></tr>
<tr><td>FMTYP</td><td>Fuel model type</td><td>Nominal</td><td>S or D</td><td>-</td></tr>
<tr><td colspan="5">Comment<i>: Static</i> (S) or <i>Dynamic (D)</i>. In <i>Dynamic</i> condition, a portion of live herbaceous fuel load is transferred into the 1-hour time-lag dead herbaceous load, depending upon the live herbaceous fuel moisture content.</td></tr>
<tr><td>FWLDOPT1</td><td>Litter fuel components by dry weight</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The litter 1-hour time-lag fuels (0 to 6.4 mm in diameter), including needles, leaves, dead herbaceous plants and fine (dead) plant parts. Usually, they are added to the 1-hour time-lag fuel load.</td></tr>
<tr><td>FWLD1H</td><td>1-hour dead fuel components by dry weight</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The 1-hour time-lag fuels (0 to 6.4 mm in diameter), including needles, leaves, dead herbaceous plants and fine (dead) plant parts.</td></tr>
<tr><td>FWLD10H</td><td>10-hour dead fuel components by dry weight</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The 10-hour time-lag fuels (0.6 to 2.5 cm in diameter), including dead medium plant parts.</td></tr>
<tr><td>FWLD100H</td><td>100-hour dead fuel components by dry weight</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The 100-hour time-lag fuels (2.5 to 7.6 cm in diameter), composed by the largest dead plant parts.</td></tr>
<tr><td>FWSRL</td><td>Live woody fuel load</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The oven-dry weight in kilograms per square meter (kg/m^2) of live woody fuel particles, consisting of fine twigs (less than 0.64 cm diameter), live shrub and tree leaves of small dimensions.</td></tr>
<tr><td>FSRSAV</td><td>Live woody fuel Surface Area - to - Volume ratio (SAV)</td><td>Numeric (2,3)</td><td>3281
-
6562</td><td>m^2/m^3</td></tr>
<tr><td colspan="5">Comment<i>:</i> The total surface area of woody plant composed by leaves, divided by the volume occupied by the plant leaves.</td></tr>
<tr><td>FWSAVD1H</td><td>1-hour dead fuel Surface Area - to - Volume ratio (SAV)</td><td>Numeric (2,3)</td><td>358
- 13123</td><td>m^2/m^3</td></tr>
<tr><td colspan="5">Comment<i>:</i> The amount of the 1-hour dead fuel surface area, divided by the volume of the specific fuel.</td></tr>
<tr><td>FWGRL</td><td>Live herbaceous fuel load</td><td>Numeric (2,3)</td><td>≥0</td><td>kg/m^2</td></tr>
<tr><td colspan="5">Comment<i>:</i> The oven-dry weight of the living annual or perennial non-woody plants, including grasses and forbs.</td></tr>
<tr><td>FGRSAVL1H</td><td>1-hour live herbaceous Surface Area - to - Volume ratio (SAV)</td><td>Numeric (2,3)</td><td>4921
- 11483</td><td>m^2/m^3</td></tr>
</table>

Comment*:* The total surface area of herbaceous plants divided by the total volume of the leaves.				
DepthL	Fuel bed depth	Numeric (2,3)	≥0	m
Comment*:* The average height of the surface fuel stratum, including litter				
MxL	Dead fuel moisture of extinction	Numeric (2,3)	5 - 100	%
Comment*:* The weighted average dead fuel moisture content at which the fuel will not sustain a spreading fire at the surface layer				
FDHC	Dead fuel heat content	Numeric (2,3)	13967 - 27934	kJ/kg
Comment*:* Represents the amount of heat energy that is included in a unit of dead fuels.				
FLFHC	Live fuel heat content	Numeric (2,3)	13967 - 27934	kJ/kg
Comment*:* Expresses the amount of heat energy that is included in a unit of live fuels				
FLWD1HC	1 – hour dead fuel moisture	Numeric (2,3)	1-60	%
Comment*:* The percentage of the 1-hour dead fuel weight that is composed by water, calculated on an oven-dry weight basis				
FLWD10HC	10 – hour dead fuel moisture	Numeric (2,3)	1-60	%
Comment*:* The percentage of the 10-hour dead fuel weight that is composed by water, calculated on an oven-dry weight basis				
FLWD100HC	100 – hour dead fuel moisture	Numeric (2,3)	1-60	%
Comment*:* The percentage of the 100-hour dead fuel weight that is composed by water, calculated on an oven-dry weight basis				
FLSRHC	Live woody fuel moisture	Numeric (2,3)	30 - 300	%
Comment*:* The percentage of the live shrub foliage and very fine stems or forbs fuel weight that is composed by water, calculated on an oven-dry weight basis				
FLGRHC	Live herbaceous fuel moisture	Numeric (2,3)	30 - 300	%
Comment*:* The percentage of the live grasses or forbs fuel weight that is composed by water, calculated on an oven-dry weight basis.				

Table 12: Advanced inputs for surface fire spread rate modelling.

Code	Description	Type	Values Range	Units
FMID	Surface fuel model code	Integer (2)	1 - 99	-
FWLD1H	Litter 1-hour dead fuel dry weight	Numeric (2,3)	≥0	kg/m^2

FLSAVD1H	Litter 1-hour dead fuel, Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWLD10H	Litter 10-hour dead fuel dry weight	Numeric (2,3)	≥0	kg/m^2
FLSAVD10H	Litter 10-hour fuel, Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWLD100H	Litter 100-hour dead fuel dry weight	Numeric (2,3)	≥0	kg/m^2
FLSAVD100H	Litter 100-hour fuel, Surface Area to Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSLD1H	Slash 1-hour dead fuel components by dry weight	Numeric (2,3)	≥0	kg/m^2
FSLSAVD1H	Slash 1-hour fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSLD10H	Slash 10-hour dead fuel components by dry weight	Numeric (2,3)	≥0	kg/m^2
FSLSAVD10H	Slash 10-hour fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSLD100H	Slash 100-hour dead fuel components by dry weight	Numeric (2,3)	≥0	kg/m^2
FSLSAVD100	Slash 100-hour fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSRD1H	Shrub 1-hour dead woody fuel load	Numeric (2,3)	≥0	kg/m^2
FSRSAVD1H	Shrub 1-hour dead woody fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSRD10H	Shrub 10-hour dead woody fuel load	Numeric (2,3)	≥0	kg/m^2
FSRSAVD10H	Shrub 10-hour dead woody fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSRD100H	Shrub 100-hour dead woody fuel load	Numeric (2,3)	≥0	kg/m^2

FSRSAVD100	Shrub 100-hour dead woody fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWSRLFOL	Shrub live foliage and fine fuel load	Numeric (2,3)	≥0	kg/m^2
FSRSAVLFOL	Shrub live foliage and fine fuel Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWGRD1H	Grass 1-hour dead fuel load	Numeric (2,3)	≥0	kg/m^2
FGRSAVD1H	Grass 1-hour dead Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
FWGRL1H	Grass 1-hour live fuel load	Numeric (2,3)	≥0	kg/m^2
FGRSAVL1H	Grass 1-hour live Surface Area - to - Volume ratio (SAV)	Numeric (2,3)	≥0	m^2/m^3
DepthL	Litter fuel bed depth	Numeric (2,3)	≥0	m
MxL	Litter dead fuel moisture of extinction (%)	Numeric (2,3)	≥0	%
DepthSL	Slash fuel bed depth	Numeric (2,3)	≥0	m
MxSL	Slash fuel moisture of extinction (%)	Numeric (2,3)	≥0	%
DepthSH	Shrub fuel bed depth	Numeric (2,3)	≥0	m
MxSH	Shrub fuel moisture of extinction (%)	Numeric (2,3)	≥0	%
DeptGR	Grass fuel bed depth	Numeric (2,3)	≥0	m
MxGR	Grass fuel moisture of extinction (%)	Numeric (2,3)	≥0	%
FDHC	Dead fuel heat content	Numeric (2,3)	≥0	kJ/kg
FLFHC	Foliage fuel heat content	Numeric (2,3)	≥0	kJ/kg
FLGRHC	Grass fuel heat content	Numeric (2,3)	≥0	kJ/kg

2.7 M31: Models for predicting future Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) using Stand Basal Area Increment

2.7.1 Introduction

Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) at forest stand level are two of the most important variables during crown fire behavior modeling. However, it is also very important to predict their potential changes through time, in an effort to quantify the associated crown fire risk, so as to implement silvicultural treatments to reduce the canopy fuel availability and to modify the vertical and the horizontal continuity of the elevated fuel stratum. On the other hand, predicting the progress of the Canopy Fuel Load and the Canopy Bulk Density over time is a rather complex task, due to the quantity and the heterogeneity of the factors that are involved in the canopy fuel accumulation rate and availability. In the absence of relevant allometric equations or any other specialized software for canopy attribute modeling and forecasting, indirect methods are required so as to estimate and evaluate potential physical changes in the canopy fuel layer over time.

The estimation of both the CFL and the CBD is currently based on allometric relationships integrating diameter at breast height (dbh) or basal area at a tree or at stand level correspondingly, according to the provided mathematical equations in Section 2.4 (M22). Based on this property, it is feasible to link the available equations with forest growth models and to account for changes in crown fuel properties through potential tree diameter alterations due to annual increments.

The available basal area forest growth models are grouped into three main categories, the empirical, the progress-based, and the hybrid models (Sun et al. 2007). The empirical models are the most widely used in forestry science and they present a large number of advantages. Their development is mainly based on the analysis of large field datasets, predicting the growth rate of a tree or a set of trees per unit area as a function of the following grouped variables:

- Age or time;
- Soil fertility or site quality;
- Competition at the stand level, usually expressed through simple or complex stand density indexes.

Usually, regression least-squares methods are used to establish species-specific tree growth models. Yet, the availability of similar models at the species level is relatively low covering only a narrow range of forest tree species worldwide. Furthermore, the complexity of the ecological process behind basal area growth leads to reduced explanations of the dependent variable’s total variance. Nevertheless, their inherent consistency has led to increased applicability over different types of forest ecosystems, focusing on forest species of increased economic and ecological value.

It is also important to mention that the proposed linkage between the available crown fuel models and forest growth systems consists of a compromised method in the absence of specified models in a wider context of the wildfire modeling framework. Hence, in statistical terms, increased residual “noise” is expected, which can lead to marginal predictions as far as the expected accuracy is concerned. On the contrary, until now this approximation is the only available solution for forecasting critical attributes of the elevated fuel stratum through passing time.

2.7.2 Relevant models

2.7.2.1 Overview and description of relevant models

The complexity of the required field data during forest growth modeling has led to a relative lack of statistical equations for basal area increment prediction. Some of the most important, along with the mathematical expressions and their inherent variables, are presented in detail in Table 13. For each of the following methods, a series of quality criteria had to be fulfilled so as to be selected for further analysis. Those criteria comprise:

- a close relevance with the basic component (basal area or stem diameter) of forest growth estimation,

- a clear reference to the three main factors of forest growth,
- a robust and applicable method to assess basal area increment over time,
- a wide range of applicability covering different types of tree species,
- an inherent simplicity to endorse their operational value.

Overall, the process of developing a forest growth model includes the following critical steps:

- Data collection of forest growth covering different species, soil qualities, regions and stand characteristics (age, species composition, silvicultural system, etc.).
- Application of selected model(s).
- Validation of the model's predictive power through coefficient of determination estimation (R^2).

The most important models and tools for this procedure are:

- Difference models (Zhang et al. 2004).
- Linear and non-linear least squares models (Fang et al. 2001, Condés and Sterba 2007).
- Generalized additive models – GAMs (Vospernik 2021).
- Artificial Neural Networks (ANN) models (Liu et al. 2003, Hao et al. 2005).
- Simultaneous equation models (Eerikäinen 2000).

The selected studies for wildfire risk assessment are briefly described in the following lines:

M31.1: In the frame of the specific study, three response components are considered for the simultaneous growth and yield model system. They were the dominant height (m), the basal area (m^2 /ha), and the total volume (m^3 /ha). The analysis showed that precise prediction of dominant height is critically important in the simultaneous system.

M31.2: Based on the stand basal diameter dynamics of artificial plantations, a significant simulating precision theory was published by Zhang and Duan (2004). According to the research conducted, the algebraic difference forms of the empirical models were applied in order to improve the simulating precision of stand basal area dynamics.

Until now, a small number of significant studies have been published covering some fire-prone pine species. Those are referred to in the following:

- For Pinus halepensis species: Trasobares et al. (2004) and Condés and Sterba (2007).
- For Pinus brutia species: Palahí et al. (2008).
- For Pinus nigra species: Vospernik 2021
- For Pinus sylvestris species: Schröder et al. 2007, Vospernik 2021

Overall, all methods are characterized by inherent simplifications, increased prediction errors, and different levels of prediction accuracy. Table 13 summarizes the most important of the above-mentioned models.

Table 13: Models for forest growth models related to basal area increment prediction, along with their variables.

Long term variables / Structural indices			**Model variables for basal area increment prediction**	
Reference	**Model**	**Forest growth component**	**Method**	**Variables**
Fang et al. (2001)	**M31.1**	Basal area increment	**$\ln(BA) = \beta_0+\beta_1/t+\beta_3\ln(h_{dom})+\beta_4\ln(nha)$**	BA = basal area per hectare t=stand age h_{dom} = dominant height nha =trees per hectare
Zhang and Duan (2004)	**M31.2**	Basal area increment	$\mathrm{H}_2 = H_1^{\frac{t_c^1}{t_c^1}} \alpha^{1-\frac{t_{c2}}{t_{c2}}}$	H_1 = the basal area at the stand age of $t1$ H2 = the basal area at the stand age of t2

			And $$H_2 = H_1\left(\frac{1-e^{-bt2}}{1-e^{-bt1}}\right)^C$$	*a*, *b* and *c* are parameters to be estimated from empirical data

2.7.2.2 *Assessment of relevant models*

A summary assessment of forest growth models focused on basal area increment prediction is provided in appendix 5.5 (Table 51).

2.8 M41: Models for climate change impact on forests

2.8.1 *Introduction*

Climate change directly impacts ecosystem services through changes in CO2 concentration, temperature, and precipitation, affecting vital processes like photosynthesis, growth, and mortality. Additionally, indirect effects emerge as climate-driven disturbances such as fire and disease interact with factors like nitrogen deposition and land-use change. Forest growth responses to climate change exhibit regional variations, with some areas witnessing increased productivity while others suffer losses. The complex nature of these changes is influenced by multiple factors including water availability, nitrogen deposition, CO2, and solar radiation. Forest managers must adapt their plans to address climate change and strive for sustainable forest management. Implementing adaptive measures reduces vulnerability and enhances resilience. Unmanaged forests are not considered climate-smart options, thus proactive adaptive management is highly recommended.

In terms of forest management, it plays a critical role in ensuring the provision of ecosystem services. At the operational level, a range of activities are undertaken, including tree thinning, pruning, and nutrient alteration. Forest managers rely on scientific tools, such as growth models, to inform their decision-making processes. These models provide a conceptual or biometric representation of real forest dynamics, varying in complexity and spatial scales. The models incorporate system parameters and state variables that change over simulations, influenced by both endogenous (internal) and exogenous (external) variables. Growth models can also account for silvicultural interventions, guiding managerial decisions. While empirical models based on inventory data have been historically used, process-based models aim to simulate the physiological processes underlying growth and their dependence on environmental conditions. Hybrid models combine features from both categories, incorporating modules that translate biological outputs into dendrometric variables of interest to forest practitioners, always considering climate conditions during calibration.

2.8.2 *Relevant models*

2.8.2.1 *Overview of relevant models*

Various growth models exist, ranging from simple empirical to complex mechanistic models. Empirical models, based on forest inventory data or tree-ring records, have been used for over 200 years but may be misleading when extrapolated to new climates and site conditions. Process-based models simulate physiological processes governing growth rate and environmental dependence. Hybrid models combine features from both categories and are calibrated for estimating parameters. For M41 models, process-based and hybrid stand-level models were classified based on structural and user-friendliness criteria. Model characteristics of 24 published models were analyzed, considering climate and management components (Table 14). Evaluation and classification were carried out using 14 sub-criteria and 29 indicators, resulting in average scores for climate, management, and use. components that are used to evaluate and categorize different growth models:

- Climate:

  - Criteria: This criterion focuses on whether the model takes into account the impact of climate on various processes.
  - Sub-criteria: CO2 concentration, Temperature, Water availability, Disturbances.
- Management:
  - Criteria: This criterion evaluates whether the model includes a range of management options.
  - Sub-criteria: Silviculture, Harvesting, Forest type.
- Use:
  - Criteria: This criterion assesses the ease of understanding and application of the model by external users.
  - Sub-criteria: Available interface, Code accessibility, Training events, technical support, User community, Updates, Spatialization, Licence, Inputs, Parameters.

Information from literature and model developers was used, with a 70% response rate. Principal component analysis was conducted to group models based on their scores in climate, management, and use variables.

Table 14: Forest growth models considered in this review, along with their spatial and temporal resolutions.

N° [Code: M41.**XX**]	**Name**	**Authors**	**Type**	**Spatial resolution**	**Temporal resolution**
1	3-PG	(Landsberg & Waring, 1997)	Hybrid	Stand	Month
2	3-PGmix	(Forrester & Tang, 2016)	Hybrid	Stand	Month
3	3-PGN-BW	(Xenakis et al., 2008)	Hybrid	Stand	Month
4	4C v2.2	(Lasch et al., 2005; Lasch-Born et al., 2020)	Process-based	Cohort	Day
5	ANAFORE	(Deckmyn et al., 2008)	Process-based	Cohort	Hour
6	BIOME-BGC	(Pietsch et al., 2003, 2005)	Process-based	Stand	Day
7	CABALA	(Battaglia et al., 2004)	Process-based	Cohort	Day
8	CASTANEA	(Dufrêne et al., 2005)	Process-based	Cohort	Day
9	FINNFOR	(Kellomäki & Väisänen, 1997)	Process-based	Cohort	Hour
10	FORCLIM	(Bugmann, 1996)	Process-based	Cohort	Month
11	FOREST-BGC	(Running & Gower, 1991)	Process-based	Stand	Day
12	FORSPACE	(Kramer et al., 2003)	Process-based	Cohort	Day
13	FORUG	(Verbeeck et al., 2008)	Process-based	Cohort	Hour

14	PNET	(Ollinger et al., 2002)	Process-based	Stand	Month/Day
15	SECRETS	(Sampson et al., 2007)	Process-based	Stand	Hour
16	TREEDYN3	(Kramer et al., 2002)	Process-based	Stand	Day
17	TRIPLEX	(Peng et al., 2002)	Hybrid	Stand	Month
18	WOODPAM	(Peringer et al., 2013)	Process-based	Stand	Month
19	CENW	(Kirschbaum, 1999)	Process-based	Stand	Day
20	GOTILWA+	(Gracia et al., 1999)	Process-based	Stand	Day
21	ecosys	(Grant et al., 2001)	Process-based	Stand	Hour
22	GO+ v3.0	(Moreaux et al., 2020)	Process-based	Stand	Hour
23	3D-CMCC-FEM LUE	(Collalti et al., 2019)	Hybrid	Stand	Day
24	3D-CMCC-FEM BGC	(Collalti et al., 2019)	Process-based	Stand	Day

2.8.2.2 Description of relevant models

3-PG (Physiological Principles Predicting Growth) is a widely recognized mathematical model for predicting forest growth. It uses a stand-level approach, considering climate, soil, and management practices to simulate forest growth. The model's annual time step allows long-term growth pattern assessment and offers outputs like stand productivity and carbon sequestration. Its flexibility allows integration with other models for comprehensive ecosystem analysis. However, the model's complexity requires careful calibration due to demanding input data requirements. Additionally, it may not fully represent mixed forests and interactions between tree species. Implemented in FORTRAN, C++, and R.

3PGmix is a complex mathematical model designed to simulate growth in mixed-species forests, capturing carbon and water dynamics. It assesses forest growth under different management scenarios, considering species interactions and stand density. However, data requirements and simplified forest structure representation pose limitations. Additional validation across various forest types is needed for enhanced reliability. Implemented in R, Python, Fortran, and C++.

3-PGN-BW BW is an extended mathematical model that incorporates soil nutritional status, enhancing forest productivity assessment. It provides valuable outputs for forest management decisions. Further development is needed to address natural mortality and competition effects on forest growth. Careful consideration is required when predicting productivity at large spatial scales using this model. Implemented in R, Python, Matlab, Fortran, and C++.

4C v2.2 is a comprehensive mathematical model for forest productivity, carbon, and water cycling, considering climate and forest management factors. It informs forest management strategies with relevant outputs. However, accurate results rely on detailed data availability, and uncertainties may arise with insufficient data or for certain forest types. The model, implemented in FORTRAN, simplifies real-world forest complexities.

ANAFORE is a mathematical model simulating forest growth, considering environmental and management factors. It aids in understanding forest dynamics but simplifies ecological processes, potentially omitting real-world complexities. Data availability and quality influence model accuracy and applicability. Implemented in Stand Pro, ForGEM, and SORTIE-ND.

BIOME-BGC is a valuable mathematical model for studying energy, water, and carbon exchange between land and the atmosphere, aiding in environmental change research. It provides insights into ecosystem functioning and the impacts of various factors. However, it may not capture all feedback mechanisms or extreme events and requires careful data validation for accurate predictions. Implemented in Fortran, C++, or MATLAB.

CABALA is a forest growth model for silvicultural decision-making, integrating carbon, water, and nitrogen flows. It assesses management options and factors like frost and drought effects. However, it may not fully represent uneven-aged stands, disturbances, or tree competition. Implementation can be complex and requires specialized knowledge. Available in CABALA-stand and CABALA-forest versions.

CASTANEA is a multi-layer, process-based model bridging soil-vegetation-atmosphere interactions for forest growth. However, its limited representation of tree species and forest processes should be considered. Spatial resolution and data availability can also pose challenges. Implemented in R and Python.

FINNFOR is a widely used forest growth simulation model predicting management and climate change impacts. It optimizes forest yields and sustainability but requires specialized knowledge for calibration. Detailed input data is essential for accurate predictions, and extreme conditions may affect its accuracy. Implemented in R and Python.

FORCLIM is a flexible forest succession model simulating stand dynamics under climate and ecological processes. It represents 180 temperate tree species and CO2 effects, valuable for studying species composition along climate gradients. However, it may not capture all ecological processes, and its spatial resolution is limited. Primarily applicable to temperate forests, it may not consider human factors or non-temperate ecosystems. Parameterization uncertainties can affect prediction accuracy. Implemented in C#, R, or Python.

FOREST-BGC is a flexible ecological model used to study climate and land-use effects on forests. However, it has limitations in parameterization, spatial resolution, and capturing small-scale disturbances. Some ecosystem processes may be overly simplified, and its applicability to all forest types is debated. Evaluating accuracy is challenging due to forest complexity. Implementations include ED model framework, Biome-BGC, or ForPEM using R and Python.

FORSPACE is a flexible mathematical model simulating tree and stand growth under various conditions. It explicitly represents ecological processes and allows customization. Assumptions of identical tree growth and simplified dynamics should be considered. Model accuracy relies on precise input data. Implemented in Fortran, C++, and R.

FORUG is a CO2 and H2O exchange model, providing NEE, TER, GPP, and evapotranspiration outputs for forest carbon and water flux assessment. However, it does not account for management effects, forest heterogeneity, or natural disturbances, limiting its representation of real-world forest dynamics. Implemented in R.

PnET is a flexible, transparent, and accessible model for forest ecosystem dynamics, informing management decisions. It focuses on key aspects of ecosystem functioning, considering carbon, water, nutrient cycles, and climate. However, input data quality affects its sensitivity and uncertainty in predictions. Limited spatial and temporal resolution may impact fine-scale applicability. Further validation is needed for accurate representation of forest dynamics and responses to management. Implemented in C# and Python.

SECRETS is a mathematical model predicting forest response to management and climate change. It aids decision-making with long-term ecosystem insights. However, site-specific data is crucial for accurate simulations, which can be challenging in data-limited regions. Implementations include FVS, SPROG, R, and Python, offering flexibility.

TREEDYN3 is a mathematical model for individual tree growth and competition, beneficial for analyzing management, carbon sequestration, and biodiversity. However, it lacks genetic diversity consideration and representation of non-tree vegetation. Modeling external factors like disturbances and climate change can be complex. It requires substantial computational power for large-scale simulations. Implemented in FORTRAN and R.

TRIPLEX is a comprehensive model for forest management, carbon budgeting, and climate change assessment. It evaluates management scenarios' impact on carbon and nitrogen dynamics and encompasses tree growth and nutrient cycling. Validation across various ecosystems and adding modules like CO2 fertilization and disturbances can enhance its accuracy. Implemented in C++.

WOODPAM is a mathematical model for studying silvopastoral ecosystems, emphasizing vegetation heterogeneity and landscape dynamics. It uses three hierarchical levels, including spatially explicit components, for detailed understanding. However, it requires detailed data, lacks representation of non-tree vegetation, and does not explicitly consider grazing in silvopastoral systems. Implemented in FORTRAN.

CENW is a mathematical model simulating individual tree growth with a process-based approach. It considers physiological processes, environmental factors, and competition. However, data availability, parameter uncertainty, and spatial scale limitations can affect model usefulness. Accurate data and parameter estimation are crucial for reliable predictions. Implemented in FORTRAN.

GOTILWA+ is a model simulating carbon and water uptake in forests under different conditions. It provides insights into carbon and water fluxes, aiding climate change and forest management understanding. Limitations include its inability to simulate mixed-species forests and lack of nutrient cycle incorporation. Horizontal spatial heterogeneity and tree height are not distinguished, affecting resource distribution estimation. Some processes rely on empirical relations, introducing uncertainties. Herbivory and insect attacks are not considered, impacting forest dynamics. Effective use requires good knowledge of the specific forest.

ECOSYS is a model simulating carbon and energy exchange between atmosphere and ecosystems, considering temperature, moisture, and radiation. It incorporates plant functional types, management, and disturbances for ecosystem insights. However, it may not account for all environmental factors and small-scale variability, limiting complexity capture. Computationally intensive, requiring significant resources and time for simulations. Implemented in FORTRAN.

GO+ v3.0 is a model simulating atmosphere-vegetation-soil interactions in managed forests, estimating carbon, water, and energy fluxes. It offers insights into forest functioning and dynamics. However, it does not account for disturbance events like fire or insect outbreaks, and assumes a homogeneous forest stand, limiting accuracy in diverse landscapes. The model's sensitivity to input parameter values requires extensive calibration for accurate predictions.

The 3D-CMCC-FEM LUE model incorporates forest structure and canopy dynamics, using LUE photosynthesis to simulate carbon cycling under environmental change. It considers light, temperature, and moisture for carbon flux estimation. However, simplifications may limit capturing full forest dynamics, and uncertainties in parameters can affect accuracy. Disturbances like fire or insect outbreaks are not explicitly included, impacting forest dynamics and carbon cycling.

The 3D-CMCC-FEM BGC model simulates forest growth and carbon cycling with detailed plant physiology and spatial processes. It offers insights into carbon sequestration and forest productivity. However, accurate input data is essential, especially for plant physiology and environmental parameters. The model assumes a static stand structure and does not account for disturbances like fire or insect outbreaks, affecting forest dynamics and carbon cycling.

EFISCEN is a model projecting forest resources for 50-60 years, addressing wood demand, forest area, and management changes. However, it suits even-aged, managed forests, and may not be suitable for uneven-aged, unmanaged, or shelterwood systems. It cannot simulate fast-growing tree species with very short rotations due to its 5-year time step. It is implemented in R code or JavaFX 2.0.

2.8.2.3 Assessment of relevant models

A general assessment of the process-based forest growth models is provided in appendix 5.5 (Table 52).

2.8.3 Relevant tools

In the preceding section, several models have been referenced, each accompanied by a set of tools designed to augment the functionalities of their respective core models. Subsequently, the following paragraphs provide a comprehensive account of the tools associated with these aforementioned models.

PnET-Succession is a C# extension of LANDIS-II, simulating tree cohort growth and incorporating PnET for water, carbon, and nutrient cycling. It offers insights into forest succession and ecosystem processes. Limitations include data availability affecting prediction accuracy, time-consuming calibration, and omission of fire, insects, and diseases, impacting forest ecosystems.

PnET-BGC is a comprehensive forest model in Microsoft Visual C++, simulating hydrology, biogeochemistry, and vegetation growth. However, it may have limited applicability to non-forest ecosystems and requires a steep learning curve. Spatial heterogeneity is not explicitly considered, affecting diverse landscapes.

3-PG Spatial is a spatial version of the 3-PG model, simulating forest productivity and carbon sequestration with spatially explicit outputs. However, it requires Arc-INFO software and has limitations in complex forest structures and mixed-species stands. Calibration and validation may be necessary for accurate predictions in novel species or regions.

3-PG for Excel is a non-spatial forest growth model in Microsoft Excel, simulating single-plot growth with graphical and tabular outputs. However, it does not support spatial modeling, relies on Excel for operations, and may require parameter calibration for accurate results.

BGC-MAN BGC-MAN, written in Java, assesses management impacts on biogeochemistry, productivity, and carbon sequestration. It offers insights into management-ecosystem interactions. However, some climate-vegetation feedbacks may not be fully accounted for. It uses GLOBIOM, EPIC, G4M, and FLAM for support in assessments and predictions.

rTRIPLEXCWFlux2 is an R package implementing a carbon-water coupling model for forest ecosystems' drought responses. It simulates photosynthesis and evapotranspiration under varying VPD and soil moisture stress. It offers insights into carbon-water coupling dynamics. However, limitations include the need for observed flux data, which may not always be available, and potential uncertainties in accounting for all influencing factors, affecting model predictions.

TRIPLEX-Management3 simulates forest growth response to pre-commercial thinning (PCT) treatments, considering diameter distribution, biomass, carbon, and nitrogen. Climate data is used as inputs. Limitations include omitting certain factors that affect growth and carbon cycling, impacting prediction accuracy. Uncertainties in data can affect result reliability.

TRIPLEX-GHG4 estimates GHG emissions from forests, simulating CH4 processes under varying environmental factors. It requires input data like meteorological, soil, vegetation, and management information. However, not all factors influencing emissions may be accounted for, and uncertainties in input data can affect results.

EFISCEN 4.1 is a Java-based forest modeling tool for simulating scenarios and assessing policy impacts on forest resources. It provides valuable inventory data and indicators for ecosystem services, supporting decision-making in forest management. However, it lacks accounting for spatial heterogeneity and may not fully consider management practices and climate change effects. It relies on national inventory data, which can vary in quality and availability.

EFISCEN Online is a web-based app for simulation and scenario assessments in forests without installation. It provides access to forest inventory data for policy and management impact evaluations at national and European levels. However, limitations include fixed settings, reliance on internet connection and browser capabilities, and shared limitations with EFISCEN 4.1 regarding data, management, and climate considerations.

EFI Tools is a collection of forest modeling tools, including EFISCEN Online, EFSOS II, ToSIA, and Bioeconomy Explorer. These tools offer various applications for forest analysis and sustainability assessment. However, limitations may include compatibility issues with browsers and devices, registration requirements, and performance variability based on internet connection and server load.

2.9 M42: Models for calculation of local weather conditions

2.9.1 Introduction

Weather forecasts of national meteorological agencies are being on the world meteorological models and then are being downscaled on national or regional scales, considering also the local conditions and data from local weather stations. Worldwide weather forecast models provide forecast usually up to 15 days. Some models provide forecast for up to one moth, nevertheless the error in the calculations can be high. Also, the Climate Forecast System v2 may provide estimates up to 9 months, although in this case it is more towards a climate prediction rather than a weather forecast.

The main worldwide weather forecast models are:

- The Global Forecast System (GFS)[1] with 28km resolution.
- The European Center for Medium-Range Weather Forecast (ECMWF/CEP)[2] which provides weather forecast for the Northern Hemisphere with resolution of 9km.
- The Global Environmental Multi-scale model (GEM)[3] Europe with a resolution of 60km at 60 degrees N.
- The UK Meteorological Office (UKMO) for global scale (10 km resolution) and Europe (2km resolution).
- The Japanese Meteorological Agency (JMA)[4] weather forecast model with a resolution of approximately 20km.
- The Icosahedral Nonhydrostatic Weather and Climate Model (ICON GLOBAL)[5] with a resolution of approximately 13km.
- The NASA/GEOS5[6] a resolution of approximately 28km resolution per pixel.

2.9.2 Relevant models

2.9.2.1 Overview of relevant models

Global weather forecast models are usually the basis for national and regional weather models. National meteorological agencies downscale the global models in order to acquire the current weather conditions. The national scale weather models can be used for planning and prevention purposes. These weather

---

[1] https://www.emc.ncep.noaa.gov/emc/pages/numerical_forecast_systems/gfs.php

[2] https://www.ecmwf.int/en/forecasts

[3] https://collaboration.cmc.ec.gc.ca/science/rpn/gef_html_public/index.html

[4] https://www.jma.go.jp/jma/en/Activities/nwp.html

[5] https://www.dwd.de/EN/research/weatherforecasting/num_modelling/01_num_weather_prediction_modells/icon_description.html

[6] https://opensource.gsfc.nasa.gov/projects/GEOS-5/

forecasts can be improved by acquiring realt0ime data from local weather stations, thus providing more robust results in the local scale.

2.9.2.2 Description of relevant models

Inputs of global weather models come from local weather station acquiring all the basic data such as temperature, wind direction, wind velocity, humidity, etc., and moreover radio soundings using weather balloons radiosondes from two to four times per day, satellites, buoys, radars, sensors on commercial aircraft and ships, coastal and river gauges.

Examples of such models at national scale that can be used for wildfires (prevention and response phase) are the following:

- BOLAM[7] 6.5km resolution mainly used by the National Observatory of Athens with main outputs of precipitation, convective precipitation, total accumulated precipitation, 10m wind, 2m temperature and snow cover every 3 hours. The model runs twice every day twice daily at the National Observatory of Athens (0000 and 1200 UTC cycles). Initial and boundary conditions come from the United Stated global model GFS (Lagouvardos et al., 2003).
- POSEIDON 2[8] resolution 5km whole Europe and Black Sea region.
- WRF[9] with a resolution of 2km used by the National Observatory of Athens and the National and Kapodistrian University of Athens with main outputs sea level pressure, precipitation, 10m wind, 2m temperature, lighting forecast, cape and snow cover evry 3hours.
- The Hellenic Meteorological Agency[10] is based on the European ECWMF and the ICON models.

2.10 M43: Models for estimating the effect of environmental factors on forest susceptibility to fire

2.10.1 Introduction

We selected the two most suitable models from chapter 2.8 - M41, which can be used for estimating the effect of environmental factors on forest susceptibility to fire, and we analyzed them using the same set of criteria, considering climate and management components.

2.10.2 Relevant models

2.10.2.1 Overview of relevant models

Table 15 provides an overview of the two selected models, which are further analyzed in the following.

Table 15: Selected forest growth models, which can be used for estimating the effect of environmental factors on forest susceptibility to fire, along with their spatial and temporal resolutions.

N°	Name	Authors	Type	Spatial resolution	Temporal resolution
M43.1	TREEMIG	(Lischke et al., 2006)	Process-based	Cohort	Year
M43.2	CENTURY v4.0	(Parton et al., 1987)	Process-based	Stand	Month

2.10.2.2 Description of relevant models

TREEMIG is a model for simulating tree species migration in response to climate change and biotic factors. It considers climate conditions, seed dispersal, and competition to predict species distribution shifts. However, it assumes free migration, oversimplifying species-environment interactions. It also overlooks

---

[7] https://www.meteo.gr/meteomaps/gr_bolam_3h_accum.cfm#

[8] https://poseidon.hcmr.gr/

[9] https://www.meteo.gr/meteomaps/about_wrf.cfm

[10] http://www.emy.gr/emy/en/index_html?

genetic variability's influence on adaptive capacity and may have biases in complex or fragmented regions due to landscape features and barriers.

CENTURY v4.0 is a process-based model focusing on carbon and nitrogen dynamics in ecosystems, simulating soil organic matter and nutrient cycling. It assesses ecosystem functioning and management impacts. However, it demands significant computational resources and may overlook some environmental drivers. It has limited applicability to specific ecosystem types and management practices and does not consider species interactions.

2.10.2.3 Assessment of relevant models

A summary assessment of the two selected models that can be used for estimating the effect of environmental factors on forest susceptibility to fire is provided in appendix 5.6 (Table 53).

2.11 M51: Models for wildfire ignition prediction

2.11.1 Introduction

One of the most significant parts of wildfire behavior modelling is the prediction of potential ignitions on a spatial basis. Despite the fact that most of the modelling efforts have been focused on wildfire's front spread rate in order to implement fire mitigation actions, the forecasting of initiation probability may lead to efficient allocation of firefighting forces along the landscape, and the timely detection of the wildfire onset for a successful suppression at early stages. Hence, understanding critical factors that determine wildfire ignitions is essential in the wider context of wildfire forest management.

The wildfire ignition risk can be termed as the probability of wildfire onset in a given area under specific conditions. In general terms, wildfire ignitions can fall into two main categories, natural-caused and anthropogenic fires, with the latest being far more frequent worldwide (Guo et al. 2016). In addition, the main factors that affect fire ignition probability can be grouped into the following categories:

- *Fuel (Fuel type / Fuel load)*. It represents the available amount of biomass for combustion, its composition in terms of fuel size, dead fuel amount, and humidity. These fuel parameters are directly related to cover type e.g. tall forest, species composition, and management type.
- *Weather conditions*. The most significant weather parameters are considered air temperature, relative humidity, and wind speed. These parameters affect the water content (humidity) of dead fuels, especially the thin fraction of them. Wind speed facilitates fire ignition and propagation.
- *Topography*. The exposure of a given location indirectly affects fuel humidity, since it determines the direct amount of solar radiation that falls on the vegetation. So, in the North hemisphere, South-faced locations are more vulnerable to fire ignitions compared to North-faced locations, due to lower fine fuel moisture contents due to higher prevailed soil and air temperatures. Altitude also affects air temperature which determines the geographical species expansion and thus fuel composition.
- *Human presence*. This factor is closely related to the likelihood of ignition due to negligent actions that are also related to the type of human activities. In addition, potential arsons cannot be also precluded. Since most fire ignitions are attributed to human actions this parameter is crucial.

2.11.2 Relevant models

2.11.2.1Overview of relevant models

Several significant research has been published aiming at modelling human and natural-caused wildfire ignitions. Since the fire ignition probability is a result of complicated natural parameters and human interaction the proposed methodologies are mostly based on decision support systems and sophisticated statistical methods, most of them mounted on Geographic Information Systems (GIS) to manage spatial variability. Overall, the processes of developing ignition prediction models follow the general order of model development.

The implementation of the developed models is usually based on the following methods:

- The Analytical Hierarchy Process (AHP) (Hysa et al. 2018).
- Artificial Neural Networks (ANN), including Random Forests analysis (de Vasconcelos et al. 2001, Vasilakos et al. 2008, Massada et al. 2013).
- The k-function and kernel estimation analyses (Genton et al. 2006, Wang et al. 2010, Guo et al. 2016).
- The logistic regression modelling approach (Krawchuk et al. 2006, Syphard et al. 2008, Catry et al. 2009, Zhang et al. 2009).
- The Maximum Entropy (Martín et al. 2019).
- Bayesian statistics and Weights of evidence (WOE)(Romero-Calcerrada et al. 2008; 2010, Ye et al. 2017).
- Spatial autoregressive model (Mundo et al. 2013).
- The χ^2 and correlation analysis (Duncan et al. 2010).

Table 16 provides an overview of models for wildfire ignition prediction, along with their variables.

Table 16: Overview of models for wildfire ignition prediction, along with their variables.

Description of models and their variables						
Model (Reference)	**Method**	**Mathematical expression**	**Variable Name**	**Description of Variable**	**Type**	**Range**
M51.1 (Hysa et al. 2018)	**AHP** (Analytical hierarchy process)	Wildfire Ignition Probability Index = 0.081**S1** + 0.158**S2** + 0.029**S3** + 0.179**S4** + 0.297**S5** + 0.037**E1** + 0.045**E2** + 0.064**E3** + 0.064**E4** + 0.030**P1** +0.017**P2**	**S1**	Distance to urban centers (m)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			S2	Distance to rural settlements (m)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			S3	Distance to main transport (m)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			S4	Distance to any road (m)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			S5	Distance to agricultural lands (m)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			E1	Solar Radiation (w/m^2)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			E2	Precipitation (mm)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			E3	Temperature (°C)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			E4	Relative humidity (%)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			P1	Slope (°)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
			P2	Orientation (°)	Numeric (2,3) / Jenks classes	>0.0 / 1-7
M51.2 (de Vasconcelos et al. 2001)	Neural Networks / Logistic regression	$\pi(x) = \frac{e^{g(x)}}{1+e^{g(x)}}$ where **g(x)**=1.5475 - 0.00054**droad** - 0.00082**durb** - 0.00239**dagri** – 0.00318**dshrub** + 0.49**southwest**	**droad**	Distance to roads (m)	Numeric (2,3)	>0.0
			durb	Distance to urban areas (m)	Numeric (2,3)	>0.0
			dagri	Distance to agriculture (m)	Numeric (2,3)	>0.0

		π(x) = probability of occurrence of ignition **g(x) =** the linear combination of the independent variables				
			dshrub	Distance to shrublands (m)	Numeric (2,3)	>0.0
			southwest	Aspect (dummy variable – class of eight directions of the compass)	Numeric (1)	1 - 8
M51.3 (Genton et al. 2006)	k-function	$K(\boldsymbol{h}) = \frac{\boldsymbol{E}(Number\ of\ events\ within\ distance\ h\ of\ any\ arbitary\ event)}{\boldsymbol{\lambda}}$ ***K(h)*** *is the k-function* ***h*** is positive and ***E*** denotes the mathematical expectation ***λ*** is the intensity of the point process (the mean number of events per unit area)	**Lightning**	Number of lightings	Numeric (2,3)	0.0092 – 10.112
			Human sources	Railroads / arson	Numeric (2,3)	0.2 – 5.3
			Fuels	Fuel type	Categorical	Palmetto – gallberry, pine, swamp, hardwood, grass, muck, other
M51.4 (Krawchuk et al. 2006)	Logistic regression	$\boldsymbol{\pi}(\boldsymbol{x}) = \frac{\boldsymbol{e}^{\boldsymbol{g}(\boldsymbol{x})}}{\boldsymbol{1} + \boldsymbol{e}^{\boldsymbol{g}(\boldsymbol{x})}}$ where **g(x)**=$4.18-2.52\mathbf{A_H}+4.40\mathbf{Sw}+2.91\mathbf{S_B}-4.74\mathbf{S^2_B}+0.23\mathbf{ln(FFMC_{JWL})}+0.27\mathbf{ln(DMC_{JWL})}+0.0012\mathbf{ELEV}+1.26\mathbf{SSR}-0.0000018\mathbf{NORTH}$ **π(x) = probability of occurrence of ignition** **g(x) = the linear combination of the independent variables**	**A_H**	Deciduous canopy dominance and greater than 25% canopy closure, up to 50% conifer by volume	Numeric(2,3)	0-8400
			S_W	White spruce canopy dominance and up to 50% other species by volume	Numeric(2,3)	0-3600
			S_B	Black spruce canopy dominance	Numeric(2,3)	0-6400
			$FFMC_{JWL}$	Joint Fine Fuel Moisture Code – lightning index	Numeric(2,3)	0-12
			DMC_{JWL}	Joint Duff Moisture Code – lightning index	Numeric(2,3)	0-13
			ELEV	Elevation at the centroid of each landscape (m)	Numeric(2,3)	227-1019
			SSR	Regional annual seasonal severity rating of fire weather	Numeric(2,3)	0.8 – 1.4
			NORTH	UTM at centroid of landscape	Numeric(2,3)	6100565 – 6428588

M51.5 (Syphard et al. 2008)	Logistic regression	$$P_i = \frac{\exp(\beta_0 + \beta_{1X1i} + \beta_{2X2i} + \cdots + \beta_{nXni})}{1 + exp(\beta_0 + \beta_{1X1i} + \beta_{2X2i} + \cdots + \beta_{nXni})}$$ **P_i = estimated probability for ignition**	**β1**	Distance development	Numeric (2,3)	Mean Euclidean distance
			β2	Distance roads	Numeric (2,3)	Mean Euclidean distance
			β3	Vegetation type	Categorical	Coastal sage scrub, northern mixed chaparral, non-native grass, oak woodland, riparian, other
			β4	Level of WUI	Categorical	None (0), low (0.01 – 0.33), intermediate (0.34 – 0.66), high (0.67 – 1.0)
			β5	January temperature	Numeric (2,3)	>0.0
			β6	Distance trails	Numeric (2,3)	Mean Euclidean distance
			β1	Distance development	Numeric (2,3)	Mean Euclidean distance
M51.6 (Catry et al. 2009)	Logistic regression	$$P_i = \frac{1}{1 + e^{-z}}$$ Where $$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_\rho X_\rho$$ **P_i = estimated probability for ignition** ***z*=the linear combination of the independent variables**	**Pop_D**	Population density (persons km^{-2})	Numeric (2,3)	>0.0
			D_Roads	Distance to the nearest road (m)	Numeric (2,3)	>0.0
			Elev	Elevation (m)	Numeric (2,3)	>0.0
			Urb	Land cover class	Categorical	1-6
			Agr	Agriculture	Categorical	1
			For	Forests	Categorical	2

		The final model was $D=166.23/(1+e^{-(-7.833+0.820Pop\_D-0.166D\_Roads+0.585Elev+2.455Urb+1.627Agr+0.388For+0.439Shr+0.426Spa)})^{2}$ **D**=Ignition density All variables but land cover are log(x+1) transformed	**Shr**	Shrub lands	Categorical	3
			Spa	Sparsely vegetated areas	Categorical	5
M51.7 (Zhang et al. 2009)	Logistic regression	$P_i = \frac{1}{1+e^{-z}}$ Where $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_\rho X_\rho$ **P_i = estimated probability for ignition** **z=the linear combination of the independent variables** The proposed model was $P_1 = 1/(1 + exp(0.022 DIS.BUIL + 0.031 DIS.VILL + 0.009 DIS.RAIL + 0.089 DIS.DIRT + 0.005 DEM - 4.383)$	**DISBUIL**	Distance to the nearest isolated building (km)	Numeric (2,3)	>0.0
			DIS.VILL	Distance to the nearest village (km)	Numeric (2,3)	>0.0
			DIS.RAIL	Distance to the nearest railroad (km)	Numeric (2,3)	>0.0
			DIS.DIRT	Distance to the dirt road (km)	Numeric (2,3)	>0.0
			DEM	Elevation (m)	Numeric (2,3)	>0.0
M51.8 (Duncan et al. 2010)	χ^2 analysis, Correlation	**Ln(strikes/ignitions)=4.5+0.11(precipitation)**	**Precipitation**	Precipitation (cm)	Numeric (2,3)	>0.0
			Lightning polarity	Negative	Numeric (2,3)	>0.0
			Vegetation	Urban/development, agriculture/rangeland, coastal strand, flatwoods, scrub, hammocks, disturbed uplands, waterways/reservoirs, estuarine water, forested wetlands, mangrove, freshwater marsh, salt marsh, disturbed estuarine wetlands, disturbed freshwater wetlands, sand/barren land, spoil, Invasive/Exotic	Categorical	1-18
M51.9 (Wang et al. 2010)	k-function	K-function and kernel estimation $K(h) = \lambda^{-1} E(.)$	**Variable 1**	Presence of air mass type thunderstorms	Categorical	
			Variable 2	Combination of topography and dominant coniferous species	Categorical	

		λ is the mean number of points per unit area, and E(.) is the expected value of the number of extra points within the distance h of an arbitary point.	**Variable 3**	Areas where agriculture, forest and forest industries coexist	Categorical	
M51.10 (Romero-Calcerrada et al. 2008)	Bayesian statistics - Weights of evidence (WofE)	Measure of the spatial association between maps of independent variables and dependent variable point data by using Bayes' probability theorem	**Variable 1**	Proximity to urban areas and roads	Categorical	
M51.11 (Romero-Calcerrada et al. 2010)	Bayesian statistics - Weights of evidence (WofE)	Choropleth mapping approach with spatial variables using Euclidian and functional distance surfaces	**Variable 1**	Human access to the natural landscape	Categorical	
M51.12 (Mundo et al. 2013)	Spatial autoregressive model	The model accounting for the spatial dependencies is $Y = X^T\beta + \lambda W(Y - X^T\beta) + \varepsilon$ $\boldsymbol{W}$ matrix is defined as the weights of spatial dependence between pixels The error terms $\boldsymbol{\varepsilon}$ of the regular regression are defined as $Y - X^T\beta$ and are weighted over the matrix $\boldsymbol{W}$ using the factor $\boldsymbol{\lambda}$ as the spatial autocorrelation coefficient.	**Topographic**	Elevation, northing, easting, slope, distance to streams, and autoregressive variable	Numeric (2,3)	>0.0
			Climatic	Precipitation, temperature and autoregressive variable	Numeric (2,3)	>0.0
			Anthropogenic	Distance to roads, distance to towns, number of town in different range of distances (2, 5 and 10 km), number of habitants in different range of distances (5, 10, 20, 30, 40 and 50 km) and autoregressive variable	Numeric (2,3)	>0.0
			Land cover	Land cover	Categorical	
			Combination	Elevation, northing, easting, slope, distance to streams, precipitation, temperature, land cover, distance to roads, distance to towns, number of town in different range of distances (2, 5 and 10 km), number of habitants in different range of distances (5, 10, 20, 30, 40 and 50 km) and autoregressive variable	Numeric and Categorical	

M51.13 (Martín et al. 2019)	Maximum Entropy algorithm (MaxEnt)	For the probability of wildfire ignition, Maxent fits a distribution $\pi(f_i)$ of the ignition points for every environmental predictor variable $f(x_j)$ at the *j-th* historical ignition point. $H = max\left\{-\sum p_k \ln{(p_k}\right\}$ $\pi(f_i) - \sum_{j=i}^{m} p_k(x_j) f_i(x_j) \leq \beta_\iota \ \ \forall f_i$ where β_i represents the empirical average of feature i and p_k is the probability distribution that is estimated for wildfire ignition risk	**Factors of socioeconomic changes**	Wildland-Urban Interface (WUI). Distance (m) to the intersection between any kind of natural vegetation susceptible to ignition and an urban-industrial construction area	Numeric (2,3)	>0.0
			Factors of traditional economic activities in rural areas.	Wildland-Agricultural Interface (WAI). Distance (m) to the intersection between any kind of natural vegetation susceptible to ignition and an agricultural and/or livestock area	Numeric (2,3)	>0.0
			Factors of potential ignition by accident or negligence.	1. Power lines (PWL). Distance (m) to the power line network 2. Roads (ROADS). Distance (m) to the road network 3. Tracks (TRACKS). Distance (m) to the forestry track network	Numeric (2,3)	>0.0
			Factors which could hamper fires.	Not protected areas or protected areas	Categorical	1 or 2
M51.14 (Vasilakos et al. 2008)	ANN	Artificial neural networks	**Fire Weather Index (FWI)**	1. Air temperature (ºC) 2. Wind speed (m/sec) 3. Relative humidity (%) 4. Rain in the last 24 h (Yes/No)	Numeric	>0.0
			Fire Hazard Index (FHI)	1. Fuel models (Flammability Index) 2. 10-h Fuel moisture content (%) 3. Elevation (m) 4. Aspect (°)	Numeric	>0.0
			Fire Risk Index (FRI)	1. Distance to primary road network (m) 2. Distance to secondary road network (m)	Numeric	>0.0

				3. Distance to power lines (m) 4. Distance to urban areas (m) 5. Distance to landfills (m) 6. Distance to recreational areas (m) 7. Distance to agricultural land (m) 8. Month (%of total fire ignitions) 9. Day of the week - Weekend or weekday (Yes/No)		
M51.15 (Guo et al. 2016)	Ripley's K-function and logistic regression (LR)	$K(h) = \frac{E(Number\ of\ events\ within\ distance\ h\ of\ any\ arbitary\ event)}{\lambda}$ ***h*** is positive and ***E*** denotes the mathematical expectation, λ is the mean number of points per unit area and $P_i = \frac{1}{1+e^{-z}}$ Where $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_\rho X_\rho$ The final model was $P_1 = 1/(1 + exp(-0.1389 - 0.0019Elev + 0.2937Dis_{road} + 0.0449Dis_{settlement} + 0.0058GST_{max} - 0.0173GST_{min} - 0.053Da_{prec} + 0.0132SSD - 0.0148Da_{RH} + 0.0001Den_{Pop} + 0.0001CGDP)$	**Elev**	Elevation (m)	Numeric	>0.0
			Dis_{road}	Distance to the nearest road (m)	Numeric	>0.0
			$Dis_{settlement}$	Distance to the nearest settlement (m)	Numeric	>0.0
			GST_{max}	Daily maximum globe surface temperature (°)	Numeric	>0.0
			GST_{min}	Daily minimum globe surface temperature (°)	Numeric	>0.0
			Da_{prec}	Daily precipitation (mm)	Numeric	>0.0
			SSD	Sunshine hours	Numeric	>0.0
			Da_{RH}	Daily mean relative humidity	Numeric	>0.0
			Den_{Pop}	Density of population	Numeric	>0.0
			GST_{max}	Per capita GDP	Numeric	>0.0
M51.16 (Ye et al. 2017)	Bayesian statistics - Weights of evidence (WofE)	Predictive dependence (**P_i**) $P_i = \frac{\exp(-1.09 + 0.571a_1 + 0.417a_2 - 0.5141a_3)}{1 + exp(-1.09 + 0.571a_1 + 0.417a_2 - 0.5141a_3)}$	**a_1**	Proximity to secondary roads	Numeric	>0.0
			a_2	Proximity to villages	Numeric	>0.0
			a_3	Proximity to farmlands	Numeric	>0.0
M51.17			**Landcover**	1. Agriculture (%)	Numeric	>0.0

(Massada et al. 2013)	Random forest*	Random Forest extends the classification trees modeling approach by averaging the predictions of many individual classification trees, each developed using a subset of the training data		2. Conifers (%) 3. Grassland (%) 4. Hardwood (%) 5. Mixed (%) 6. Riparian (%)		
			Anthropogenic	1. Distance to nearest structure (m) 2. Distance to nearest road (m) 3. Structure density, 1 km radius (km^1)	Numeric	>0.0
			Topographic	1. Elevation (m) 2. Slope (°) 3. South-westness	Numeric	>0.0

2.11.2.2Description of relevant models

The selected models for wildfire ignition are briefly described in the following:

M51.1 In the frame of the specific study, the proposed Wildfire Ignition Probability Index (WIPI) in broad-leaved forests was estimated using the Analytical Hierarchy Process and a number of independent variables that were clustered in three main classes. The introduced model was partly aiming to generate indexing maps categorizing the broad-leaved forest surfaces by their Wildfire Ignition Probability Index.

M51.2 The main objective of this study was to develop and to validate models for the prediction of spatially distributed probabilities of wildland fire ignitions in central Portugal. A logistic regression approach along with neural networks were used to develop models by exploring relationships between ignition location/cause and values of geographical and environmental variables.

M51.3 A spatial-temporal structure of wildfire ignitions in Florida was analyzed using the *L-function* and the relative clustering index was defined for summarizing the amount of clustering over various spatial scales. The method is based on the assumption that information about clustering can be used to effectively manage wildfires.

M51.4 A logistic regression method was used to describe variation in annual initiation occurrence in Alberta, Canada over 11 years. The independent effects of weather and forest composition on lightning fire initiation patterns were quantified, to demonstrate how these biotic and abiotic components contribute to ecosystem dynamics in the mixed-wood boreal forest.

M51.5 Human and biophysical explanatory variables were used to model and map the spatial patterns of both fire ignitions and fire frequency in the Santa Monica Mountains, California. To that end, a multiple logistic regression model was developed and predictive maps of fire ignitions and fire frequency were created.

M51.6 In the frame of the study, logistic regression models were implemented to predict the likelihood of ignition occurrence, using a set of potentially explanatory variables, and producing an ignition risk map for the Portuguese mainland. The analysis was based on several ignitions that occurred in Portugal during a 5-year period.

M51.7 Based on logistic regression analysis a predictive model of the probability of human-caused ignition of grassland fires in the east of Inner Mongolia, China was developed, using topography, distances, and weather factors as predictor variables. The analysis was based on data of 2611 fires during 1977–1996.

M51.8 Sixteen years of lightning data (1986–2003, excluding 1987 and 2002) were used to quantify the relationship between lightning incidence and ignitions on Kennedy Space Center, Merritt Island National Wildlife Refuge, and Cape Canaveral Air Force Station. In order to achieve that, χ^2 analysis was performed to determine if ignition and lightning frequencies occurred more or less than expected for each land-cover class, while Pearson correlation analysis was performed to investigate the relationship between the number of lightning strikes and the number of fires.

M51.9 The *K-function* and kernel estimation methods were used to evaluate the spatial and temporal patterns of ignition locations of lightning- and human-caused forest fires in Alberta, Canada. According to the authors, such quantitative knowledge could lead to the development of fire response and fire-suppression strategies appropriate to specific regions within the province.

M51.10 In the frame of the study, the weights of evidence (WofE) model from Bayesian statistics was implemented to examine the causal factors of wildfires in the southwest of the Madrid region for two differently defined wildfire seasons, and predictive maps of wildfire risk were developed. The authors claimed that the WofE model is useful for estimating future wildfire risk.

M51.11 Based on the Weights of Evidence model, ten predictive maps of wildfire risk were created in order to study the effect of biophysical and socioeconomic factors on wildfire risk in Madrid region, Spain. It was also suggested that the models produced from a choropleth mapping approach with spatial variables using Euclidian and functional distance surfaces are the best of the ten models.

M51.12 Through the suggested method, a fire ignition database was used to conduct a comprehensive analysis of the spatial pattern of fire ignitions in the western area of Neuquén province, Argentina, for the 1992 - 2008 period in order to better understand the spatial pattern and the environmental drivers of the fire ignitions, with the ultimate aim of supporting fire management. A spatial autoregressive model was implemented, and the developed fire ignition probability maps can be used to inform wildfire management strategies in the western area.

M51.13 By applying the Maximum Entropy algorithm (MaxEnt), and based on wildfire data from 2008 to 2011, GIS and remote sensing data for the explanatory variables, eight occurrence data scenarios were constructed. The model's accuracy was tested by using a cross-validation *k-fold* procedure and an operational validation with 2012 data.

M51.14 A back-propagation neural network (BPN) was implemented to distinguish the influence of each examined variable in a fire ignition risk scheme for Lesvos Island in Greece. In addition, four different methods were utilized to evaluate the three fire danger indices within the above scheme and the partial derivatives method showed the best performance in ranking variables' importance.

M51.15 In this study, the spatial pattern and drivers of forest fire in Fujian province, China was analyzed, during 2000 - 2008 using Ripley's *K-function* and logistic regression (*LR*) model. In addition, the likelihood of fire occurrence was mapped based on the resultant model, while fire ignitions, weather conditions, vegetation, topography, infrastructure, and socioeconomic factors were extracted from ArcGIS environment.

M51.16 Through the current study, a Bayesian weights-of-evidence (WofE) method was developed based on fire hotspots in China's Yunnan province extracted from satellite images and verified as known wildfires for the period 2007–2013. In addition, a set of factors that impact fire ignition as associated with human accessibility was considered and a posterior probability was calculated. The precision was validated using samples of both presence and absence by withheld validation data.

M51.17 One parametric, statistical model (Generalised Linear Models, GLM) and two machine-learning algorithms (Random Forests and Maximum Entropy) were used to predict ignition probabilities. Despite similar model performance and variables, the map of ignition probabilities generated by Maxent was markedly different from those of the two other models.

Overall, all methods are characterized by inherent simplifications, applicability constrains and different levels of prediction accuracy.

2.11.2.3 Assessment of relevant models

A summary assessment of models that can be used for wildfire ignition prediction is provided in appendix 5.7(Table 54).

2.12 M61: Enhancement of forest resilience through forest management treatments

2.12.1 Introduction

The improvement of forest resilience to fire can be fulfilled by reducing fire-burning characteristics as well as by retarding or even preventing the fire from traveling from one part of the forest to the next. The factors that affect fire-burning conditions are the vegetation, the climate and meteorological conditions, and topography. The only one of these factors that can be altered by humans, on a large scale, is the vegetation. The reduction of forest fire-burning characteristics, such as the type of fire, the flame length, and the energy released in the fire front, can be accomplished through "forest fuel" modifications (Albini and Reinhardt, 1995; Dimitrakopoulos, 2002; Alexander et al, 2004; Agee and Skinner, 2005; Molina et al 2011; Ager et al, 2023).

Forests are considered as ecosystems consisting of various structural elements and they are affected by both, external environmental factors and internal forest factors (EF) (e.g., forest stand structure). These factors interact dynamically and they may change through time and space. A classification of the EF factors can be made based on their Biotic or Abiotic nature as well as their origin as depicted in Table 17.

Table 17: Classification of Environmental and Forest (EF) factors based on their origin (Kaloudis, 2008).

Biotic			Abiotic		
Flora	**Fauna**	**Human**	**Climate**	**Soil**	**Landscape**
- species structure and composition, - plant pests.	- animals, - birds, - insects, - microorganisms.	- logging, - fire risk, - pollution, - deforestation.	- air temperature and humidity, - wind speed, - duration and direction of the wind, - type, amount, and distribution of precipitation, - sunshine duration.	- depth, pH, - organic matter content, - porosity, - mechanical composition, - stone content, - erosion.	- altitude, - slope, exposure, - position, - site quality index.

Viewing the forest as an ecosystem is a key concept in forest science, and based on this perspective the forest should be managed in a way that protects all its major ecological components. In addition, its multifunctionality should be protected and its ecosystem services to be maintained. Therefore, the modification of the composition and the structure of the forest is a complex task, and it cannot be carried out by assuming that a simple biomass load reduction is adequate. In addition, individual interventions to modify the forest biomass are highly costly and for this reason, they cannot be applied on large spatial scales.

In contrast, modifying the characteristics of forest biomass through locally adapted forest management offers a comprehensive solution that maintains forest multifunctionality and at the same time can increase its resilience to fires. Furthermore, the cost reduction of applying silvicultural treatments may be achieved by including them in the overall planning of harvesting woody biomass, in a framework of multiuse forest management. The harvested biomass is associated by a significant economic value and part of this value is attributed to the amortization of harvesting cost. The cost of additional silvicultural treatments, that may be required to improve the resilience of the forest, such as the removal of logging residues, can be included in the cost of the management, while the owner may benefit from the utilization of the additional biomass that is harvested.

In this context, for the improvement of forest resilience through forest management, two major steps are followed. The first one is the definition of the main and secondary objectives of forest management including the improvement of forest resilience and the second one is the selection of the silvicultural treatments, in order to fulfil the objectives of forest management. In addition, the determination of fire risk level per forest management unit is critical. The forest management units can be set as a stand size or be determined according to the variability of EF factors and fire risk. Since the fire risk level is a composite environmental index, it can significantly vary across the forest landscape and especially in the WUI locations. The estimation of the fire risk values, as well as of other composite EF factors can be greatly facilitated by the use of models presented in this report (e.g., M22 and M23).

Since the EF factors vary through space and time, their representation should be taken into consideration for the planning period, according to their nature:

- The representation of the spatial variability/interaction of EF factors/functions could be facilitated through the use of a spatial referenced raster model. This type of representation allows the adaptation of a forest management size unit according to the variability of EF factors providing better accuracy and effectiveness of the applied silvicultural treatments.
- The representation of the temporal variability in EF factors/functions, especially those related to fire risk and forest resilience to fire, can be classified either as progressive through time (e.g, timber volume), as periodic (e.g., fire risk), or as constant / time-independent (e.g., topography).

2.12.2 Decision support model for enhancing forest resilience through forest management treatments

The available mechanical treatments in the forest layers for the reduction of fire risk, as they emerged from the forest practice and the literature, are described below and they are usually applied at different scales of intensity. Also, a short description of the advantages and disadvantages of each treatment is provided.

- ***Removal of logging residues***: This treatment reduces the surface fuel load and therefore the characteristics of the fire. It is noted, however, that its intensive application may cause a lack of nutrients in the forest ecosystem in the long-term application (Kalabokidis and Omi, 1998; Gibbons, 2000; Scherer et al. 2000; Smith et al., 2000; Zabowski, et al., 2000; Baeza et al., 2002; Theodoropoulos et al., 2002; Fernandes and Botelho, 2003; Carter and Foster, 2004; Peterson et al., 2004).
- ***Tree pruning***: Reduces the likelihood of surface fires turning into crown fires while improving the quality of timber produced.
- ***Understory thinning***: This treatment modifies the fire characteristics of the fire by reducing the availability of the ladder fues. In combination with the tree pruning, the possibility of crown fire is significantly reduced. Overthinning may increase soil erosion.
- ***Thinning of the forest canopy***: By reducing the horizontal continuity of the forest canopy, it reduces fire characteristics and helps determine the type of fire. In addition, it affects forest production by improving the quality of timber and facilitating the regeneration of the forest. It is noted that excessive thinning reduces the amount of timber produced and the productivity of the forest, allows the development of unwanted rich understorey, can degrade the aesthetic value of the forest, and increases the risk of soil erosion (Graham et al., 1999; Baldwin et al., 2000).

In case of application of any of the abovementioned silvicultural treatments, it is considered that the harvested combustible materials do not participate in a possible future fire. This assumption presupposes that the harvested vegetation is handled appropriately, such as by burning in the forest at an appropriate time or through their total removal from the forest.

Other forest interventions, according to the literature, can increase forest resilience to fire, and are presented in what follows.

- ***Encouraging species with high fire resistance*** **(ESHFR)**: This refers to the effect of favouring native broadleaf forest species implementation and growth, which increase the resistance of the forest to fires, due to the high moisture content of their foliage (Graham et al., 1999; Baldwin et al., 2000; Dimitrakopoulos et al., 2001; Dimitrakopoulos and Panov, 2001; Dimitrakopoulos, 2001a; Dimitrakopoulos, 2001b; Dimitrakopoulos, 2002; Dimitrakopoulos and Dritsa, 2003; Liodakis et al., 2003). Broadleaf species, when mixed in coniferous forests, also increase the resistance of these forests to insects and pathogens and improve the aesthetics of the landscape.
- ***Grazing of domestic animals***: Reduces the surface fuel load (bushes and herbs) and contributes to the increase of agricultural income, through the production of livestock products (Bachelet et al., 2000; Valderrabano and Torrano, 2000; Torrano and Valderrabano, 2005; Liedloff et al., 2001).
- ***Construction of fuel breaks***: Reduces the spread of fires (Omi, 1996; Butler and Cohen, 1998a; Agee, et al., 2000). In general, the purpose of firebreaks is to reduce the potential fire spread rate,

providing the opportunity for a successful suppression to fire fighting crews. According to Butler and Cohen (Omi, 1996; Butler and Cohen, 1998a; Butler and Cohen, 1998b), the distance between the fire front and the fire brigades must exceed four times the estimated maximum height of flame produced in order to provide adequate protection to fire brigades against fire. Therefore, assuming that the estimated height of the flame is *FH* and the required width of the firewall is *D* then it must hold:

$$D \geq 4FH \tag{1}$$

However, in this case, the width of the fuel brake zone is considered as very large. Due to both the associated implementation and maintenance cost, as well as the impacts on the ecosystem and its aesthetic value, the creation of similar fuel breaks is avoided in practice and it is recommended only in cases of protecting elements of significant value. To reduce the negative effects of wide fuel breaks, a fuel break configuration consisting of parallel subzones is sometimes preferred. More specifically, for a typical fuel break constructed along a road, the following three subzones are proposed (Kaloudis, 2008), heading from the forest to the road:

- *Shrubby vegetation*: This subzone is covered by shrubby vegetation or some young trees of small height. Periodically, and if necessary, based on the maximum height of the flame produced in this subzone, thinning of vegetation shall be carried out to remove high vegetation.
- *Herbaceous vegetation*: This subzone is covered by herbaceous vegetation.
- *Fine Vegetation*: This subzone does not carry any kind of vegetation and must remain constantly free of vegetation or other flammable materials.

The sub-zones are arranged in such a way that those with the smallest fire characteristics are located on the side of the fire brigades, i.e. on the side of the access road. Therefore, it applies:

$$(FH_{i+1} - FH_i) > 0 \tag{2}$$

At the same time, it is required that the sum of the widths of each of the sub-zone(s) on the side of the road or protected area must be greater than four times the height of the flame of the sub-zone to the side of the forest.. Therefore, if FH_i is the estimated height of the flame in sub-zone *i* and D_i its amplitude, then it must apply:

$$\sum_{i=1}^{n} D_i \geq 4FH_{n+1} \tag{3}$$

for n = 1,2,3.

It follows from these formulas that for i = 1,2,3, the width of sub-zone *i* must satisfy the condition:

$$D_i \geq 4(FH_{i+1} - FH_i) \tag{4}$$

In some rare cases, where the height of the flame in a sub-zone (i) is greater than that of the sub-zone (i+1), then either this subzone is abolished (equation 5), or the vegetation is modified appropriately, so that the relationship (1) applies.

$$(FH_{i+1} - FH_i) \leq 0 \quad \Big| \quad D_i = 0 \tag{5}$$

Adapted firebreaks, such as the layout on only one side of the road, are proposed for the protection of settlements, public benefit institutions and public utility projects.

The advantages of the above complex form of fuel break compared to the simple, fine vegetation zone are the following:

- the aesthetic deterioration of the landscape is significantly reduced,
- the soil erosion/loss is reduced,

- the maintenance costs are reduced, since deforestation of the entire area occupied is not required and partial control of vegetation can be achieved by grazing,
- its creation is more easily accepted.

Alternative treatments can also be used to further strengthen forest fire resistance (Kaloudis et al., 2001). In particular, the natural regeneration is very sensitive after a fire, due to immaturity for seed production. Based on this fact, it is recommended to maintain an appropriate number of Sower trees, those with the best phenotype, until the young stand can produce seeds..

The intensity of application of each of the forest treatments presented above is affected by the values of EF factors/functions (Omi and Kalabokidis, 1998; Stephens, 1998; Fried, 2000; Tiedemann et al., 2000; Shang et al., 2004; Stephens, 2004; Agee and Skinner, 2005; Knapp et al., 2005; Stephens and Moghaddas, 2005a; Stephens and Moghaddas, 2005b; Stephens and Moghaddas, 2005c; Ohlson et al., 2006). Conceptually, the solution to the problem of choosing the forest treatments and their intensity to fulfil the main and secondary objectives of forest management is based on a mapping between causal EF factors and their relative properties and values over the forest functions. This is depicted in Table 18. In particular, each row of Table 18 contains an EF factor and each column contains a forest treatment. An up arrow (down arrow) indicates that, when the value of an EF factor increases, the intensity of forest treatment application increases (↑) (decreases) (↓) respectively. The dash (-) indicates that there is no change.

Table 18: Influence of certain forest/environmental factors on the intensity of application of forest treatments (Kaloudis, 2008).

Treatment Factor	Forest thinning	Branch pruning	Animal grazing	Slash removal	Understory thinning	Reinforce-ment ESHFR
Fire risk	↑	↑	↑	↑	↑	↑
Regeneration success	↑	-	-	↑	-	-
Soil erosion risk	↓	↓	↓	↓	↓	-
Ecological value	↓	↓	↓	↓	↓	-
Aesthetic value	↓	↓	-	-	-	-
Site quality	-	↑	-	-	-	↑

2.13 M62: Models of biodiversity index and ecological site classification

2.13.1 Introduction

According to Yang et al. (2021), biodiversity is the variety of life, including variation among genes, species and functional traits. Key biodiversity indicators include: richness, as a measure of the number of unique life forms; evenness, as a measure of the equitability among life forms; heterogeneity, as the dissimilarity among life forms (Cardinale et al. 2012).

Biodiversity index is a quantitative measure or estimate of biodiversity state in a certain area and time interval, indexes can inform on different dimensions of biodiversity, including taxonomic and functional diversity, or the state of ecosystems and communities, and be used to compare areas, scenarios, and to monitor change. (Gonzales et al. 2023)

For Biodiversity index, it would be easier if biodiversity could be measured by the quantity of birds in a forest, wildflowers in a meadow or beetles in a log. Unfortunately, the simplicity is not one of the virtues of biodiversity (Noss and Cooperrider 1994). Ecosystems are more complex then we can imagine. A common misconception is that biodiversity is equivalent to species diversity, more species in an area, it means greater its biodiversity. For biodiversity, the quality is more important than quantity. It is not so much in number of species but in its identity (Hill et al. 2005). For example, fragmenting old growth forest with clear cut, would increase species richness at local scale but not contribute to species richness at a broader scale if sensitive species were lost from the landscape (Noss and Cooperrider 1994). Diversification can all too easily become homogenization. The greatest cause of homogenization is the introduction of non-native species of plants and animals, often called exotics. Exotics are species that have invaded new areas due to accidental or deliberate transport by human. In many cities and also in the campus, those exotics have been commonly found due to deliberately planted or released it. The exotics polluted the native flora and fauna, but their contribution was nothing to biodiversity. Regions invaded by exotics lose their distinctive characters, the results is global impoverishment (Noss and Cooperrider 1994). In spite of many tools and data sources, biodiversity remains difficult to quantify precisely.

If environmental changes occur, a uniform population of a single species of plant acclimated to a certain habitat is more vulnerable. A population with a greater diversity of plant species has a better chance of containing individuals who can adapt to changes in the.

Current studies prevalently apply three main methods to measure biodiversity: calculating the number of species; Shannon’s diversity index; and emergy method (systemic approach environment). (Yang et al. 2021)

An ecological site is a distinctive kind of land with specific soil and physical characteristics that differs from other kinds of land in its ability to produce distinctive kinds and amounts of vegetation, and in its ability to respond similarly to management actions and natural disturbances. Unlike vegetation classification, *ecological site classification* uses climate, soil, geomorphology, hydrology, and vegetation information to describe the ecological potential of land areas. A particular ecological site may feature several plant communities (described by vegetation classification) that occur over time and/or in response to management actions.

An overview of existing indices, methods, models and tools is provided, which are used for biodiversity index and ecological site classification. Literature sources include the scientific publications registered in the following databases: Scopus, Science Direct, Web of Science, Springer Link, and Science Open databases. Multiple keywords were used to find the most relevant literature sources. The documents were identified with advanced search query strings such as “(Biodiversity OR Biodiversity index OR Diversity) AND (Ecological site classification OR Forest site classification) AND (Method OR Model OR Tool OR System)”. The different keywords used were based on the various subjects that characterize the main research topic.

2.13.2 Relevant models

2.13.2.1 Overview of relevant models

Table 19 provides an overview of models that can be used for calculating biodiversity and for ecological site classification.

Table 19: Overview of forest models for calculating biodiversity and for ecological site classification.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities of the Model	Restrictions of the Model
M62.1	Calculating the number of species	Experimental	C	Based on the consideration of ecosystem size. Depends on the counts of species.	Methodological limitations related to quantity description and

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities of the Model	Restrictions of the Model
					comparison for the needs of biodiversity conservation.
M62.2	Shannon's Diversity Index	Index	C	Considers both species richness and evenness	Two limitations: the original application of the Index was determined by the assessment of internal flows in ecosystems; and the Index ignores the hierarchical structure of ecosystem food web and assumes an equal weight to all of its components.
M62.3	Emergy method	Mathematical	C	System approach to measure biodiversity index by a linear optimization technique to calculate conversion coefficients (transformities) of components in ecosystem food networks.	It is still undermined by the lack of accurate population data for various species, and due to the huge differences in lifetimes of species and uncertainties of how large is the area that supports the species, the calculation of the emergy required to support a species may be subjected to very large uncertainties.
M62.4	NTM	Mathematical	C	Simple and quick tool to assess the biodiversity of plant species.	It is only available in collaboration projects, there is

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities of the Model	Restrictions of the Model
					no user-friendly interface.
M62.5	Single factor site classification systems	Empirical	C	Describes a forest site, such as soil or climate, whereas multifactor classifications are based on interrelationships between climate, physiography, soil (and related edaphic factors) and vegetation.	Not specified
M62.6	Multifactor site classifications	Empirical	C	Based on interrelationships between climate, physiography, soils and vegetation.	Not specified
M62.7	Phytocentric approach	Empirical	C	Uses a phytometer as a relative indicator of the productivity of a forest ecosystem.	Limitations of site index. Site index is not applicable to uneven-aged or mixed-species forest stands or bare land; it is species-specific and cannot be used for other species even on the same site.
M62.8	Geocentric approach	Empirical	C	Uses climatic and soil factors as predictors that primarily affect plant growth and development. As these factors can be spatially linked, potential site productivity for a given tree species can be predicted and mapped at the landscape level.	Not specified
M62.9	Phytogeocentric approach	Empirical	C	Uses both causes and effects variables in a holistic manner in	Not specified

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				order to classify forest site productivity.	

2.13.2.2 Description of relevant models

Biodiversity index calculation methods/models

Shannon's diversity index is a popular tool for landscape diversity calculation (Dušek & Popelková, 2012). The most advantage of the Shannon's index is easily comparable due to numerical value characteristics of the index.

The index is calculated using the formula H = -Σ(pi * ln(pi)), where pi is the proportion of individuals belonging to the ith species and ln is the natural logarithm (Gotelli & Colwell, 2001). A higher value of the Shannon index indicates higher diversity in the community.

Shannon Index = $-\sum_{i=1}^{m} P_i \log P_i$

The Shannon evenness index, also known as Pielou's evenness index, is a measure of the distribution of relative abundance among species in a community (Soininen et al. 2011). It is calculated by dividing the Shannon index by the natural logarithm of the species richness, resulting in the formula J = H/log(S), where H is the Shannon index and S is the number of species. The Shannon evenness index ranges from 0 to 1, with 1 indicating perfect evenness and 0 indicating maximum unevenness.

Shannon Evenness Index = $\frac{-\sum_{i=1}^{m}(P_i \log P_i)}{\log m}$

Where P_i is the relative proportion of area in comparison with total area, *log m* is the maximum value in the logarithm patch area.

Both the Shannon index and Shannon evenness index are widely used in ecological research to assess and compare biodiversity in different communities and ecosystems. They provide valuable information about the composition and structure of species assemblages and can be used to monitor changes in biodiversity over time or in response to environmental disturbances (Gotelli & Colwell 2001).

Calculating the number of species (abundance), based on the consideration of ecosystem size, typically depends on the counts of species. There still exist methodological limitations related to quantity description and comparison for the needs of biodiversity conservation (Brown et al. 2006). First limitation is related to a biodiversity database compiled from multiple data sources with various sampling intensities which may lead to diverse focuses, resulting in collection bias or observations with different confidences (Fagan and Kareiva 1997). Second limitation is related with the fact that biodiversity determined by counting the number of species could mislead the selection of biodiversity hotspots, e.g., some correlations were found between plant and animal species richness. While areas with high plant species richness do not always coincide with regions with high richness at other nutritional levels, such as animals and microorganisms (Mares 1992). Therefore, such a determination may miss other areas of great conservation significance (Mares 1992, Kareiva and Marvier 2003). Furthermore, applying biodiversity as an indicator of ecosystem services to design conservation strategies, multiple definitions of biodiversity (such as different definitions based on taxonomy, species and genetics) make the indicator-based targets ambiguous, which may confuse conservation priorities (Angermeier and Karr 1994). Moreover, the correlation between the number of species in an ecosystem and the value of its ecosystem services is not clear. In fact, too little empirical evidences support this opinion, although Tilman and Downing (1994) found that each time the investigated grassland ecosystem loses a species, the drought tolerance of the grassland would be greatly affected. Several studies proved that ecosystem processes are mainly determined by functions of organisms rather than populations (Leps et al. 1982). For example, the differences in the response of five adjacent grasslands in northern England to frost, drought and fire can be predicted from the functional characteristics of the dominant vegetation, unrelated to the population of vegetation (Grime 1997, MacGillivray and Grime 1995, Schwartz et al. 2000). It indicated a biodiversity conservation project solely based on species richness rather than comprehensive consideration of the entire evolution of species would fail to identify the most crucial habitats for the conservation of species genetic information (Smith et al. 1993). In addition, some researchers claimed that simply calculating the number of species in a region cannot reveal the ecological interactions and feedback structures that produce ecosystem characteristics such as productivity, stability, etc. (Worm and Duffy 2003).

The **Shannon's Diversity Index** was proposed by ecologists to address the limitations of the approach based on calculating the number of species. They proposed a diversity index derived from information theory to re-characterize biodiversity (Brown et al. 2006), i.e., considering both species richness and evenness (Shannon 1948). However, the applications of the Shannon's Diversity Index have two limitations, making it hard to effectively predict ecosystem characteristics such as stability, adaptability, productivity, etc. First, the original application of the Index was determined by the assessment of internal flows in ecosystems (MacArthur 1955). In particular, energy and material flows (at trophic level) were assessed to quantify the information transfer among species. However, due to the unavailability of flow data, the Index applies stocks (extensive variables, such as readily available data of biomass) instead of flows to measure biodiversity, which is inconsistent with basic logics in information theory (Ulanowicz 2001). The second limitation is that the Index ignores the hierarchical structure of ecosystem food web and assumes an equal weight to all of its components. Under this circumstance, given a fixed number of ecosystem components with equal probability, the Shannon's Diversity Index is the largest. That is to say, the even distribution of species stocks would increase biodiversity. However, according to the Lindeman's Effect theory, the energy transfer efficiency among species in food web varies, even among species at the same trophic level. Therefore, it would be misleading to conclude the maximum biodiversity stems from maximum uniformity. This indicates the Shannon's Diversity Index calculated by physical stocks of species is applicable to species at a single trophic level instead of diverse trophic levels (Brown et al. 2006). However, even if a physical flow (i.e. energy or carbon) is applied to measure the Index, the uniformity of the flow is not an expected condition for the entire food web, since a physical flow geometrically decreases as the trophic level increases (Brown et al. 2006).

Emergy method was developed to address the limitations of previous approaches to biodiversity calculation (Odum, 1996). The term emergy means the total available energy, directly and indirectly required to produce a product or a service. It is a new system approach to measure biodiversity index by a linear optimization technique to calculate conversion coefficients (transformities) of components in ecosystem food networks. Such an approach represents two notable improvements: addressing the expected distribution of physical population at different trophic levels and explaining the distribution of flow class in ecosystem food web. This approach is referred to as emergy-based dynamic accounting method for biodiversity maintenance. Odum (1996) used the emergy-based static method to account biodiversity maintenance. He argued that biodiversity and emergy are interrelated, since biodiversity would increase proportionally with the increase in renewable emergy in a system. Through emergy it is possible to quantify the resources needed to support species. A larger number of emergy flows maintain more species in a system, thus increasing its complexity. The emergy required for the transmission of genetic information for a species is generally high because genetic information evolves over time and needs larger amounts of inputs (Lee et al. 2013, Lanfear et al. 2014). The circulation of genetic information is the essence of the entire biological evolution process and requires driving energy based on solar one. When an ecosystem includes more species, it needs more solar energy to support interactions among species in each cycle process (Campbell and Tilley 2016). The simplest way to reduce biodiversity is the loss of an individual species. Odum (1996) regarded the average emergy required to maintain the existing species on Earth as the emergy used by each species during its life cycle, then divided by the total number of species during this period. By calculating the specific turnover time of a species and the emergy input to support the species in an area, the emergy inputs to maintain the species can be obtained. This method also has some limitations. First, it is still undermined by the lack of accurate population data for various species. Second, due to the huge differences in lifetimes of species and uncertainties of how large is the area that supports the species, the calculation of the emergy required to support a species may be subjected to very large uncertainties. Therefore, data availability remains a key bottleneck for a reliable measurement of this kind. However, since the maintenance of the genetic material cycle of species in an ecosystem requires the availability of (solar) energy, this method links local renewable resources and biodiversity, and provides a way to calculate the biodiversity potential maintained by ecosystem through the emergy of local renewable resources. This is called emergy-based static accounting method for maintaining biodiversity. Both static and dynamic methods measure biodiversity potential in an ecosystem. (Yang et al. 2021)

NTM is a simple and quick tool to assess the biodiversity of plant species. It can help to evaluate the effect of external and internal pressures on ecosystems. Pressures may be changes of land use and management, climate change, flooding or nitrogen deposition. The model can be used for policy evaluation and for assessing effects of management on nature. The model provides a biodiversity index value for plant diversity, based on the red list criteria for plant species. The biodiversity index is linked to three abiotic parameters for nutrient availability, groundwater table and soil acidity. When these three parameters are given as input together with the ecosystem type (heath, forest or grassland), it will calculate an index value. The higher the index value, the higher the chance of presence of red list species. The model is often used as an end tool for model evaluations of nature policy in combination with e.g. VSD+ SUMO. The model needs as inputs the ecosystem type and the values for nutrient availability, soil acidity and groundwater table. The model has been calibrated for the river Rhine delta. If it is used outside that area a calibration set of vegetation plots is necessary and a list of nature conservation values per species based on the red list criteria. NTM is a point model for the local/regional scale. It is only available in collaboration projects, there is no user friendly interface. (Delta Alliance 2023)

Ecological site classification methods/models

Site classification for forestry falls broadly into two groups: single factor or multifactor methods (Savill 1983).

Single factor site classification systems rely on one factor to describe a forest site, such as soil or climate, whereas multifactor classifications are based on interrelationships between climate, physiography, soil (and related edaphic factors) and vegetation. Classifications based on soil characteristics are the most common single factor systems used in forestry, mainly due to the abundance of soil survey information. Indicator plants or plant communities have also been used for the basis of site classification (Cajander 1929, Anderson 1961, Krajina 1969, Ellenburg 1988, Klinka et al. 1989, Pyatt et al. 2001, Wilson et al. 1998, 2001 and 2005). The characteristics of the vegetation can be used as an indicator of the fertility and moisture status of a forest site. The classification of site fertility based on indicator plants and plant associations is highly developed in British Columbia, Canada, where it is used to quantify the soil moisture and soil nutrient regime of forest sites (Green and Klinka 1994). A strong relationship between the inherent soil nutrient status and vegetation type and abundance has been found in recent research carried out in Scotland (Wilson et al. 2001 and 2005) and this has formed the basis for the indirect assessment of soil nutrient and moisture regimes soil in the Ecological Site Classification (ESC) system developed for Britain.

Multifactor site classifications are based on interrelationships between climate, physiography, soils and vegetation. An example of a multifactor classification is provided by Anderson (1961), who developed a classification based on the abundance of certain plant communities on a site. Fertility classes A to F reflect decreasing fertility levels and increasing degrees of wetness, from Dry to Wet with Peat. For each combination of fertility and moisture class, Anderson recommended selection of tree species based on their nutritional and moisture requirements. This was based on his extensive experience as a forestry practitioner in Britain and Ireland. Condon (1961) devised a multifactor classification for blanket peats, based on vegetation, topography, and peat characteristics. In recent years multifactor classifications have achieved prominence in forestry as they focus on ecological site quality and its relation to the ecosystem. These systems are considered more robust, so are expected to provide a sound basis for the sustainable forestry production of wood and the provision of other forest benefits (Pojar et al. 1987, Green and Klinka 1994, Pyatt 1995).

Other general approaches to Forest Site Classification used to assess forest site productivity introduced Pokharel and Dech (2011). Those can be broadly categorized into three approaches: phytocentric (Leary 1985), geocentric (Leary 1985), and phytogeocentric.

The **phytocentric approach** uses a phytometer as a relative indicator of the productivity of a forest ecosystem. There are numerous factors that comprise the environmental complex that ultimately affects plant growth and development; therefore, integrating their combined effects by measuring attributes of the plants themselves is a very practical way to assess the site effect (Hills 1952; Davis et al. 2005). To date, the phytocentric approach has been widely used in quantifying forest productivity; despite the fact that it is restricted in use to an area with vegetation cover present. Site index (Jones 1969; Carmean 1975; Hägglund 1981), site form (Vanclay and Henry 1988), site productivity index (Huang and Titus 1993), growth intercept (Bull 1931) and indicator species (Cajander 1926; Carmean 1975; Daniel et al. 1979) are methods that use characteristics of the existing vegetation as an indicator of site productivity. Here we will focus our examination on site index, which is the most widely used phytocentric approach to site productivity assessment in the forest ecosystems of North America (Jones 1969; Carmean 1975; Hägglund 1981; Kayahara et al. 1998; Stearns-Smith 2001; Pokharel and Froese 2009). Site index is the mean height of dominant or co-dominant trees at a reference age. The main reasons for the advocacy of height as a measure of site productivity were due to its simplicity, ease of application, wide applicability, freedom from the effect of density and high correlation to volume yields (Mader 1963). There are also numerous limitations of site index. Site index is not applicable to uneven-aged or mixed-species forest stands or bare land. Site index is species-specific and cannot be used for other species even on the same site. Species-specific conversions have been developed, but these conversions further compounded the bias from site index estimates (Nigh 2002).

The **geocentric approach** uses climatic and soil factors as predictors that primarily affect plant growth and development. As these factors can be spatially linked, potential site productivity for a given tree species can be predicted and mapped at the landscape level (Gustafson et al. 2003; Monserud and Huang 2003). Such flexibility makes the geocentric approach an attractive alternative over the phytocentric approach from the perspective of large-scale integrated planning and management of forest resources. Depending on the scale of management being considered, and the availability of different data layers, various spatial factors can be related to forest productivity on the landscape. Climate characteristics such as rainfall, temperature, radiation and wind are essential site factors (Hägglund 1981; Avery and Burkhart 2002). Soil characteristics such as moisture, texture, depth, nutrient availability and soil temperature have a significant influence on tree growth; however, this effect depends on the species and soil type (Husch et al. 1982). Due to this relationship between soil properties and tree growth, soil characteristics are considered to be important variables when evaluating site productivity at the stand level (Grigal 2009).

The **phytogeocentric approach** uses both causes and effects variables in a holistic manner in order to classify forest site productivity. Such an approach utilizes the totality of site that is governed by its biotic, climatic and soil conditions as related to its capacity to produce vegetation (Hills 1960; Spurr and Barnes

1980). As a result, both environmental and biotic factors, which account for the dynamic processes within a forest ecosystem, and change with environmental conditions and disturbance regimes over time, are included in the classification scheme.

2.13.3 Field case applications

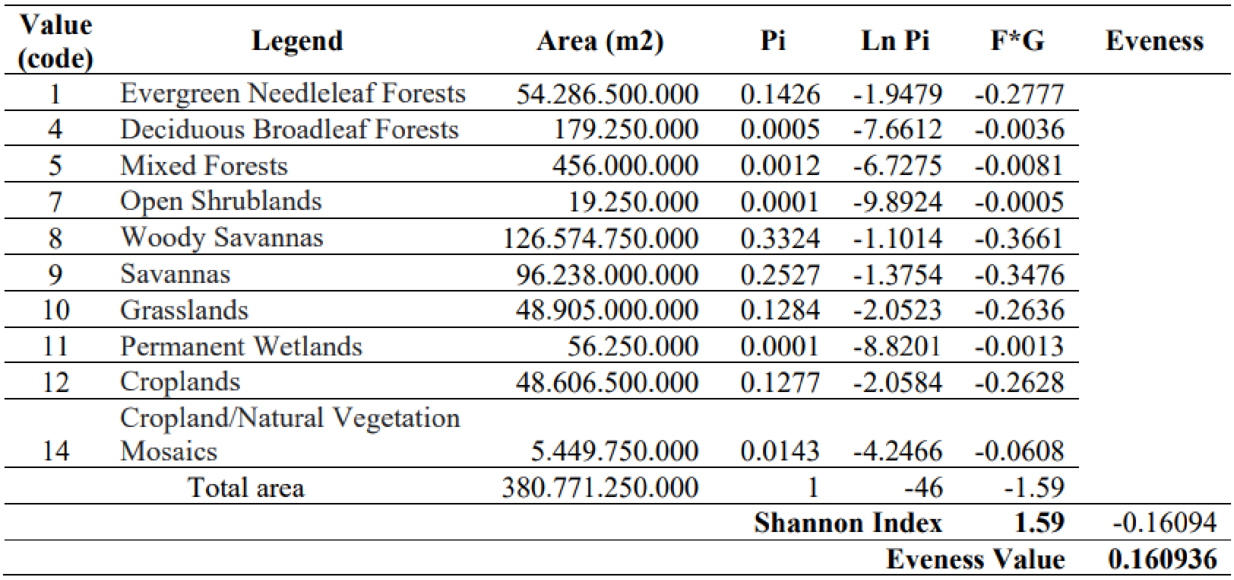
Biodiversity calculations utilizing the Shannon Index and Shannon Evenness Index were conducted in three distinct locations: Cova de Beira (Portugal), Podpol'anie (Slovakia), and Gargano (Italy). These biodiversity assessments were based on data sourced from Global Land Cover MODIS MCD12Q1.061. The MODIS Global Land Cover data boasts a spatial resolution of 500 meters and a temporal resolution of 1 year. In each of the three areas, the calculations yielded varying Shannon Index and Shannon Evenness Index values on an annual basis.

For instance, in the year 2016, Cova de Beira displayed a Shannon Index value of 1.59 and a Shannon Evenness Index of 0.16. However, by 2017, these values had shifted to 1.58 for the Shannon Index and 0.233 for the Shannon Evenness Index. This dynamic reveals a decline in the Shannon Index value accompanied by an increase in the Shannon Evenness Index. It's important to note that a higher Shannon Index value signifies greater diversity, and similarly, a higher Shannon Evenness Index value indicates greater evenness.

Notably, in the case of Cova de Beira and Gargano, the decrease in the Shannon Index was correlated with an increase in the Shannon Evenness Index. Conversely, in other instances, such as in Podpolanie during 2006 and 2007, an increase in the Shannon Index was observed alongside an increase in the Shannon Evenness Index.

Table 20 and Table 21 provide the calculation of the Shannon Index and the Shannon Evennes Index in Cova de Beira for years 2016 and 2017, respectively, whereas Figure 3 and Figure 4 depict the corresponding land cover distribution. Table 22 and Table 23 provide the calculation of the Shannon Index and the Shannon Evennes Index in Podpol’anie 2006 and 2007, whereas Figure 5 presents the land cover distribution for year 2006. Table 24 and Table 25 provide the calculation of the Shannon Index and the Shannon Evennes Index in Gargano for years 2018 and 2019, respectively.

Table 20: Calculation of Shannon Index and Shannon Evennes Index in Cova de Beira 2016.



Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	54.286.500.000	0.1426	-1.9479	-0.2777	
4	Deciduous Broadleaf Forests	179.250.000	0.0005	-7.6612	-0.0036	
5	Mixed Forests	456.000.000	0.0012	-6.7275	-0.0081	
7	Open Shrublands	19.250.000	0.0001	-9.8924	-0.0005	
8	Woody Savannas	126.574.750.000	0.3324	-1.1014	-0.3661	
9	Savannas	96.238.000.000	0.2527	-1.3754	-0.3476	
10	Grasslands	48.905.000.000	0.1284	-2.0523	-0.2636	
11	Permanent Wetlands	56.250.000	0.0001	-8.8201	-0.0013	
12	Croplands	48.606.500.000	0.1277	-2.0584	-0.2628	
14	Cropland/Natural Vegetation Mosaics	5.449.750.000	0.0143	-4.2466	-0.0608	
	Total area	380.771.250.000	1	-46	-1.59	
			Shannon Index		**1.59**	-0.16094
					Eveness Value	**0.160936**

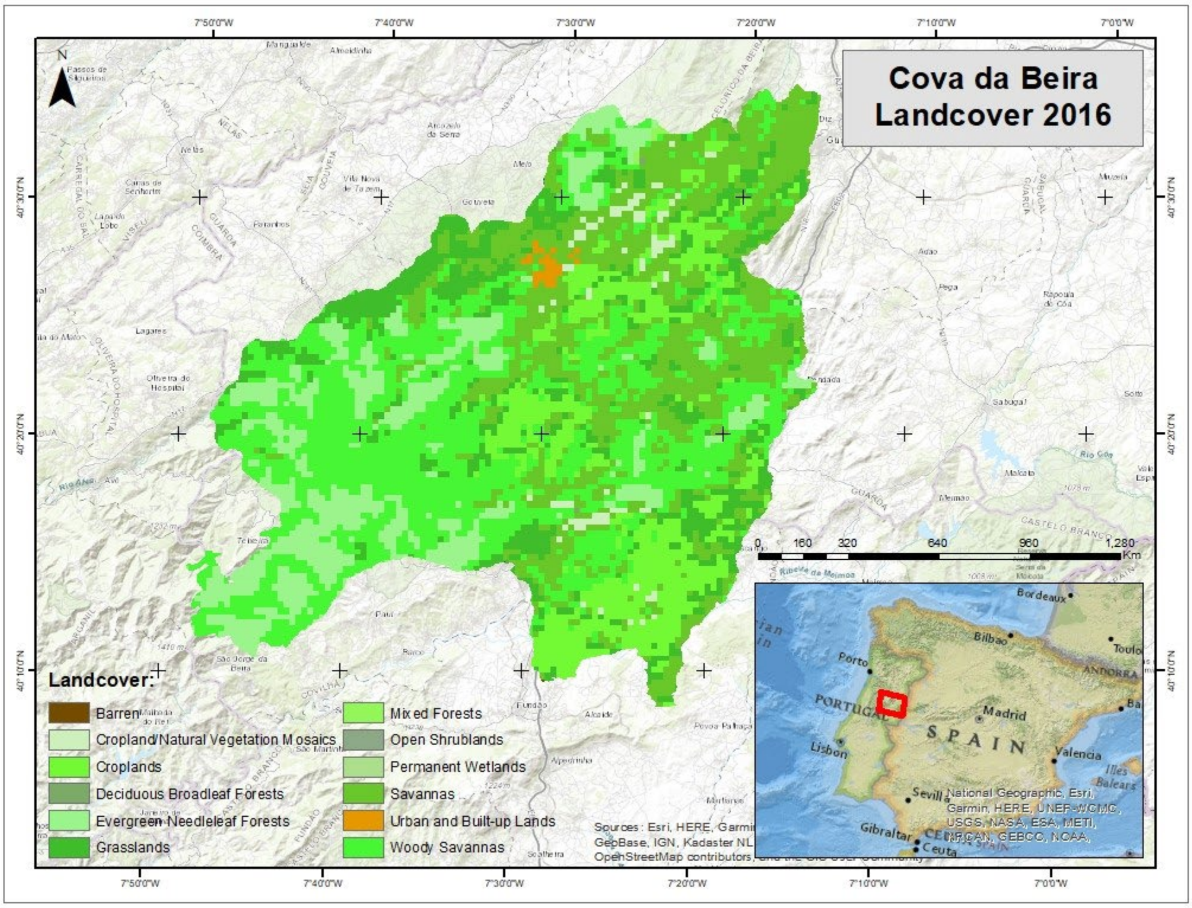


Figure 3: Land cover distribution in Cova de Beira 2016.

Table 21: Calculation of Shannon Index and Shannon Evennes Index in Cova de Beira 2017.

Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	47.978.000.000	0.1267	-2.0656	-0.2618	
4	Deciduous Broadleaf Forests	171.500.000	0.0005	-7.6995	-0.0035	
5	Mixed Forests	427.250.000	0.0011	-6.7867	-0.0077	
7	Open Shrublands	186.250.000	0.0005	-7.6170	-0.0037	
8	Woody Savannas	122.911.750.000	0.3247	-1.1249	-0.3652	
9	Savannas	99.749.000.000	0.2635	-1.3337	-0.3514	
10	Grasslands	60.380.250.000	0.1595	-1.8357	-0.2928	
12	Croplands	42.495.000.000	0.1123	-2.1869	-0.2455	
14	Cropland/Natural Vegetation Mosaics	4.245.000.000	0.0112	-4.4906	-0.0504	
	Total area	378.544.000.000	1	-35	-1.58	
			Shannon Index		**1.58**	-0.23311
				Eveness Value		**0.23311**

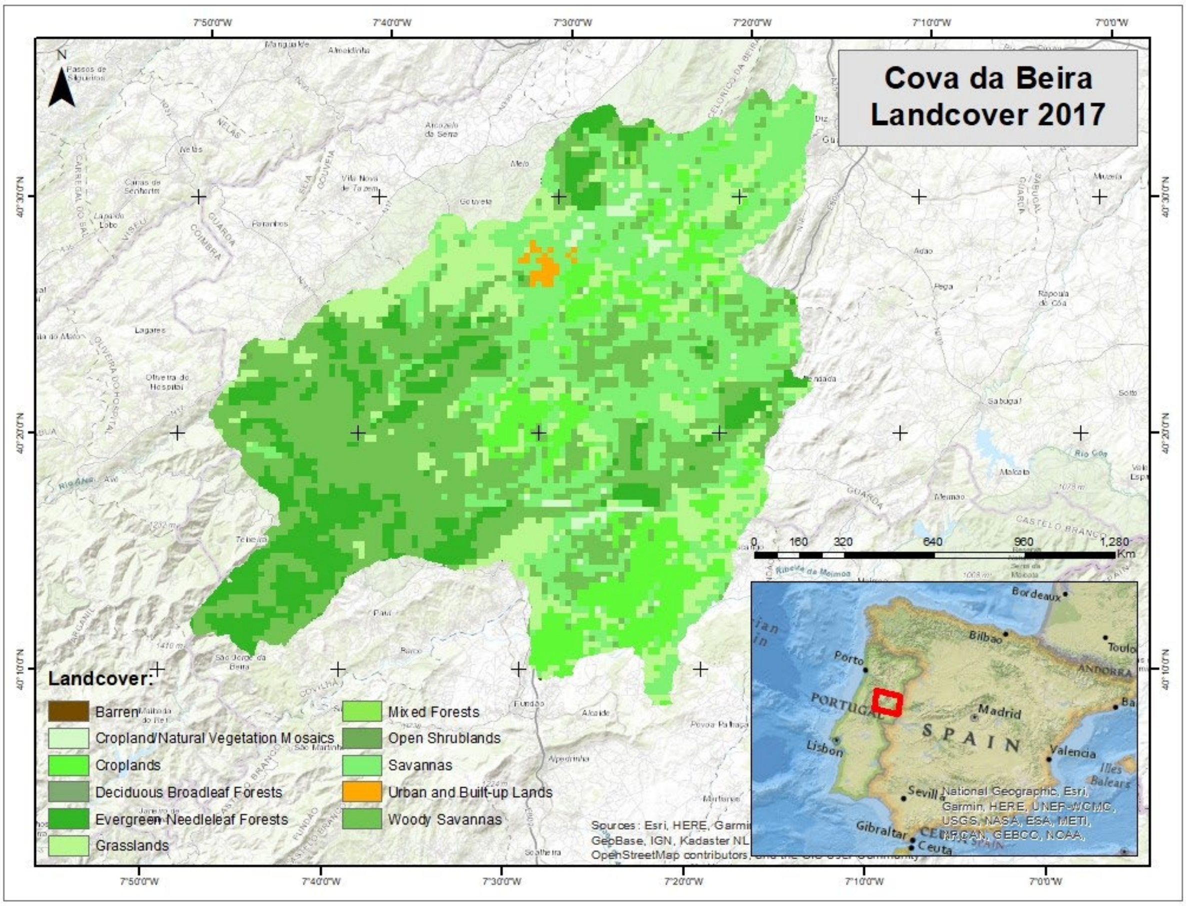


Figure 4: Land cover distribution in Cova de Beira 2017.

Table 22: Calculation of Shannon Index and Shannon Evenness Index in Podpol'anie 2006.

Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	54.286.500.000	0.1634	-1.8114	-0.2960	
4	Deciduous Broadleaf Forests	179.250.000	0.0005	-7.5246	-0.0041	
5	Mixed Forests	456.000.000	0.0014	-6.5909	-0.0090	
8	Woody Savannas	19.250.000	0.0001	-9.7559	-0.0006	
9	Savannas	126.574.750.000	0.3811	-0.9648	-0.3676	
10	Grasslands	96.238.000.000	0.2897	-1.2388	-0.3589	
11	Permanent Wetlands	48.905.000.000	0.1472	-1.9158	-0.2821	
12	Croplands	56.250.000	0.0002	-8.6836	-0.0015	
14	Cropland/Natural Vegetation Mosaics	5.449.750.000	0.0164	-4.1101	-0.0674	
	Total area	332.164.750.000	1	-43	-1.39	
				Shannon Index	**1.39**	-0.14219
					Eveness Value	**0.23311**

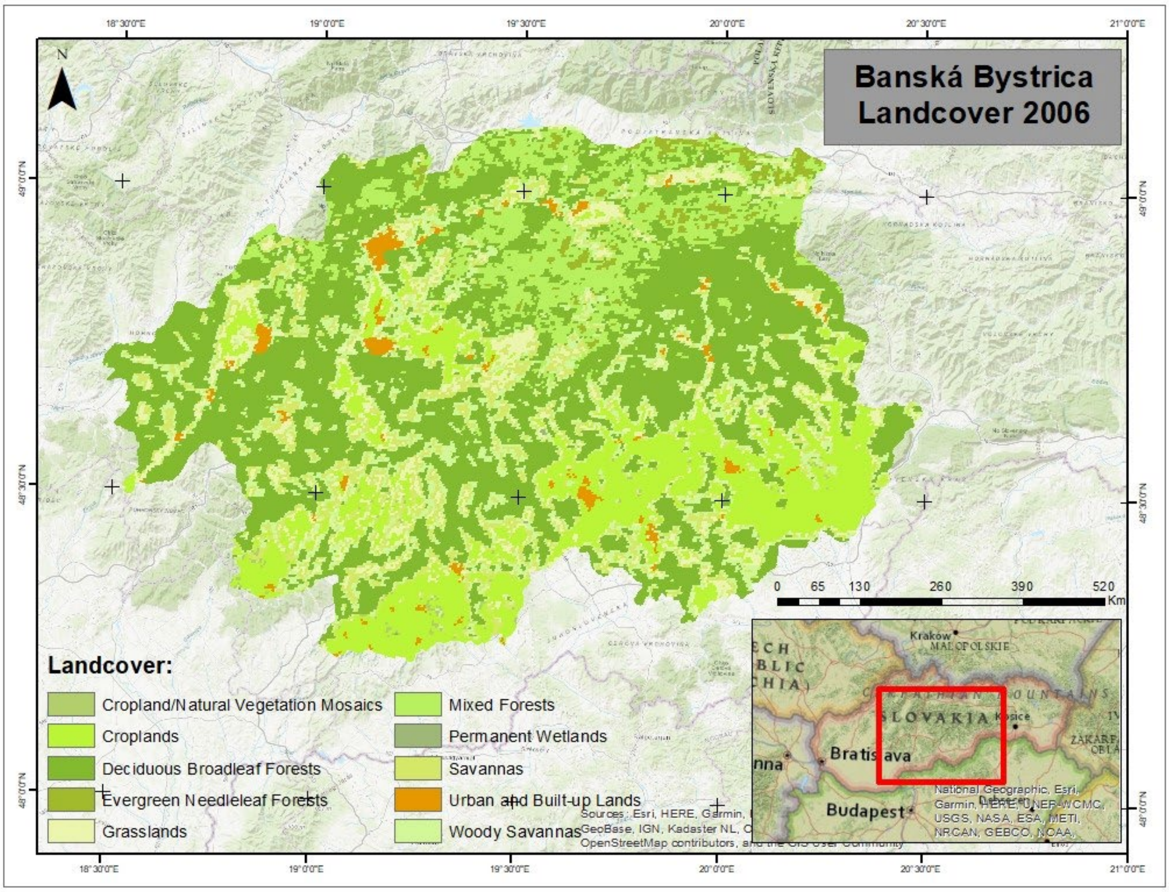


Figure 5: Land cover distribution in Podpol’anie 2006.

Table 23: Calculation of Shannon Index and Shannon Evenness Index in Podpol’anie 2007.

Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	38.542.500.000	0.0147	-4.2167	-0.0622	
4	Deciduous Broadleaf Forests	1.127.030.000.000	0.4312	-0.8411	-0.3627	
5	Mixed Forests	259.265.500.000	0.0992	-2.3106	-0.2292	
8	Woody Savannas	308.743.000.000	0.1181	-2.1359	-0.2523	
9	Savannas	243.350.500.000	0.0931	-2.3740	-0.2210	
10	Grasslands	185.521250.000	0.0710	-2.6453	-0.1878	
11	Permanent Wetlands	5.93.000.000	0.0002	-8.3910	-0.0019	
12	Croplands	4.437.40.250.000	0.1698	-1.7732	-0.3011	
14	Cropland/Natural Vegetation Mosaics	67.46.500.000	0.0026	-5.9594	-0.0154	
	Total Area	26.135.32.500.000	1	-31	-1.63	
				Shannon Index	**1.63**	-0.19469
					Eveness Value	**0.19469**

Table 24: Calculation of Shannon Index and Shannon Evenness Index in Gargano 2018.

Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	27.772.750.000	0.0597	-2.8182	-0.1683	
2	Evergreen Broadleaf Forests	30.146.750.000	0.0648	-2.7361	-0.1774	
4	Deciduous Broadleaf Forests	52.711.250.000	0.1133	-2.1774	-0.2468	
5	Mixed Forests	5.134.000.000	0.0110	-4.5063	-0.0497	
7	Open Shrublands	228.750.000	0.0005	-7.6173	-0.0037	
8	Woody Savannas	61.382.250.000	0.1320	-2.0251	-0.2673	
9	Savannas	79.593.000.000	0.1711	-1.7653	-0.3021	
10	Grasslands	75.724.750.000	0.1628	-1.8151	-0.2955	
11	Permanent Wetlands	9.713.750.000	0.0209	-3.8687	-0.0808	
12	Croplands	119.879.000.000	0.2578	-1.3557	-0.3495	
14	Cropland/Natural Vegetation Mosaics	2.799.500.000	0.0060	-5.1128	-0.0308	
	Total Area	465.085.750.000	1	-36	-1.97	
			Shannon Index		**1.97**	-0.25886
					Eveness Value	**0.25886**

Table 25: Calculation of Shannon Index and Shannon Evenness Index in Gargano 2019.

Value (code)	Legend	Area (m2)	Pi	Ln Pi	F*G	Eveness
1	Evergreen Needleleaf Forests	25.941.500.000	0.0558	-2.8864	-0.1610	
2	Evergreen Broadleaf Forests	28.987.500.000	0.0623	-2.7754	-0.1730	
4	Deciduous Broadleaf Forests	53.104.250.000	0.1142	-2.1700	-0.2478	
5	Mixed Forests	4.657.250.000	0.0100	-4.6038	-0.0461	
7	Open Shrublands	408.750.000	0.0009	-7.0369	-0.0062	
8	Woody Savannas	58.070.000.000	0.1249	-2.0806	-0.2598	
9	Savannas	86.467.500.000	0.1859	-1.6825	-0.3128	
10	Grasslands	74.787.500.000	0.1608	-1.8276	-0.2939	
11	Permanent Wetlands	10.194.750.000	0.0219	-3.8203	-0.0837	
12	Croplands	119.903.750.000	0.2578	-1.3555	-0.3495	
14	Cropland/Natural Vegetation Mosaics	2.563.000.000	0.0055	-5.2010	-0.0287	
	Total Area	465.085.750.000	1	-35	-1.96	
			Shannon Index		**1.96**	-0.27887
					Eveness Value	**0.27887**

2.13.4 *Relevant tools*

2.13.4.1 *Overview of relevant tools*

Table 26 provides an overview of tools used for calculating biodiversity or for ecological site classification.

Table 26: Overview of tools used for calculating biodiversity or for ecological site classification.

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
T62.1	Ecological site classification	Not specified	C	afforestation management,	Needs to be used in the context of a

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				climate change impact, ecological classification, fertilization, forest ecology, species selection, yield prediction	well-formulated conservation strategy. The process needs to be rigorous.
T62.2	Forest Vegetation Simulator	Windows	C	biomass estimation, carbon sequestration, climate change impact, fire behaviour, forest fuel harvesting, forest vegetation management, silvicultural regime	Any number of projection units (stands) can be processed in a simulation. There is a limit of 500 plots or points in any projection unit. There is a limit of 40 time period 'cycles' for any simulation, but the length of the cycles can be controlled by the user.
T62.3	FORSITE	Not specified	C	prediction of future forest stand development under climate change, definition of different treatment types.	Requires sound database for tree species choice.
T62.4	SIBYLA	Windows	C	simplified index of total diversity, ecological site classification, freeware	It is to be used for non-commercial activities.
T62.5	Landscape DSS	Windows	C	Biodiversity (including ecological fire groups, Wet forest, ecological refuges, Leadbeater possums and Greater Gliders)	Not specified.
T62.6	NED-2	Windows, ArcGIS	C	Carbon	Not specified.

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
T62.7	GISCAME	Not specified	C	High conservation values	Oriented on forest types, not for specific species.

2.13.4.2 Description of relevant tools

EcologicalSiteClassification (ESC) is a PC-based DSS that supports a methodology for the evaluation of the suitability of different tree species and woodland communities as defined in the National Vegetation Classification (NVC) for Great Britain, and also predicting yield in the form of a site index, on the UK forest land. This tool encourages the decision makers on the election of a suitable forest species according to their site soil properties and climatic data, instead of selecting an inadequate species and then trying to modify site characteristics to make it more suitable. It also provides the suitability of the species according to the expected evolution of the climate, and predicts the potential yield in the form of a site index. The number of tree species considered is 25, and there are also 20 native woodland types. The site information is linked to ESC suitability models for 20 of the 25 NVC woodland communities (W1-W20) and 25 species of tree using a 'fuzzy membership function' approach. (Reynolds et al. 2008)

Forest Vegetation Simulator (FVS) is a family of forest growth simulation models. The FVS GUI is the graphical user interface for the FVS software. Running in a web browser, FVS enables the user to read inventory data, perform simulations with and without management, and analyze the results. Forest managers have used FVS extensively to summarize current stand conditions, predict future stand conditions under various management alternatives, and update inventory statistics. Output from the model is used as input to forest planning models and many other analysis tools. In addition, FVS has been linked to other Forest Service corporate software such as databases and geographic information systems. Uses of FVS are not restricted to timber management applications. Other uses of FVS include considering how management practices affect stand structure and composition, determining suitability of stands for wildlife habitat, estimating hazard ratings for insect outbreaks or wildfires, and predicting losses from fire and insect outbreaks. The typical projection unit in FVS is a stand, but the size of the projection unit is not limited. Many stands may be included in a simulation, alllowing analysis at the level of the smallest project, such as a thinning on several acres, all the way up to the watershed and landscape level, such as a national forest plan. The entire FVS system is a collection of models. There are separate models for things like tree growth, mortality, regeneration, understory vegetation, fire, fuels, wood volumes, carbon, biomass, insects, diseases, and economics. A model to simulate the effects of climate change is also in development. Things like habitat suitability and risk to a particular pest can be easily calculated or inferred from the FVS outputs. Any number of projection units (stands) can be processed in a simulation. The FVS software system is comprised of the FVS geographic variants, model extensions, and a graphical user interface. There is a limit of 500 plots or points in any projection unit. There is a limit of 40 time period 'cycles' for any simulation, but the length of the cycles can be controlled by the user. (US Forest Service 2023)

FORSITE provides forest site classification which is based on a GIS-based geo-ecological stratification model. The database is based on a digital elevation model, a geological base map, digitally available site and climate data as well as empirical site parameters. A map of forest types is derived based on several thematic maps, including information about energy, water and nutrient balance. Those parameters are modeled on the basis of point and area related data, which are then combined into forest types with a uniform combination of factors. The model allows a stratification of the forest types on all sites based on digital geo-ecological parameters. In addition to the ecological facts, each forest type is characterized by a description of silvicultural guidelines containing information on the appropriate choice of tree species, potential hazards and adaptation methods. These guidelines also describe previous experiences with the tree species and their mixtures, and will provide recommendations for the future forest management with regard to climate change. (Vacik et al. 2019)

Simulator of forest biodynamics (SIBYLA) belongs to the category of tree growth simulators (hereinafter called as a growth simulator). It is a simulator that strives to imitate the behavior of trees in the context of forest ecosystems. It consists of the set of mathematical models and algorithms that are transformed into an integrated software package SIBYLA Suite. In the growth simulator SIBYLA, site quality classification is used instead of forest yield classes. Site quality is evaluated directly from ecological site characteristics: climate, air, and soil. The ecological characteristics are called site variables. They directly influence the production capacity of a stand (tree height and diameter increment). The growth simulator SIBYLA uses the model of ecological classification applied in the growth simulator SILVA 2.2, which was derived by Kahn (1994). In the growth simulator SIBYLA, tree species and structural components of forest stand biodiversity are assessed. In the case of tree species diversity, tree species richness, heterogeneity, and evenness are determined. In the case of structural diversity, horizontal and vertical structure and its differentiation are assessed. At the same time, a simplified index of total diversity is calculated. Considering the nature of the characteristics, they are calculated only for the stand as a whole (simulation plot), not for individual stand components and tree species. It provides mathematical models and calculation to estimate the tree species richness, heterogeneity, evenness, horizontal and vertical structure, structure differentiation and total diversity. (TUZVO 2023)

Landscape DSS assists land managers and communities to explore potential changes in multiple landscape values associated with fire regimes, changing climate, and alternative management practices. is a prototype knowledge and evaluation system that, when fully developed will assist land managers and communities to explore potential changes in multiple landscape values associated with fire regimes, changing climate, and alternative management practices. This DSS utilizes two models to assess changes in landscape values – the fire regime simulator FROST and the forest landscape vegetation dynamics model LANDIS-II. Each year FROST first simulates fire in the landscape in response to particular climate, suppression, and prescribed burning inputs. LANDIS-II then simulates changes in forest structure and composition over time in response to this fire and LANDIS-II modelled harvesting (i.e. it enacts vegetation mortality, regeneration, and growth), and then feeds this vegetation information back into FROST for a successive fire year. These yearly FROST and LANDIS-II outputs are also fed into FRAPPE (part of the FROST Family software). FRAPPE uses modelled algorithm(s) to analyse how these outputs impact different landscape values of interest. These landscape values include: Biodiversity (including ecological fire groups, Wet forest, ecological refuges, Leadbeater possums and Greater Gliders); Carbon; Experienced High Conservation Values; Infrastructure loss (e.g., roads, powerlines, industrial building, hospitals); People and House loss; Geometric Mean of Species Abundance; Shannon's diversity and Fractal dimension index; Soil Erosion Rates; Major Water Contamination Events; Visual aesthetics viewshed. In this way, the DSS brings together fire regimes and landscape vegetation changes to explore how changes in future climate and management practices may impact on important landscape values. (FLARE Wildfire Research 2023)

NED-2 is a Windows-based system designed to improve project-level planning and decision making by providing useful and scientifically sound information to natural resource managers. Resources currently addressed include visual quality, ecology, forest health, timber, water, and wildlife. NED-2 expands on previous versions of NED applications by integrating treatment prescriptions, growth stimulation, and alternative comparisons with evaluations of multiple resources across a management unit. The NED-2 system is adaptable for small private holdings, large public properties, or cooperative management acros multiple ownerships. NED-2 implements a goal-driven decision process that ensures that all relevant goals are considered; the character and current condition of forestland are known; alternatives to manage the land are designed and tested; the future forest under each alternative is simulated; and the alternative selected achieves the owner's goals. NED-2 is designed to link with the NedLite package for field data collection using a handheld PDA, and is constructed to be easy to link to third-party applications. The NED process is being field tested to demonstrate its utility and identify weaknesses. The resource goals addressed by NED include timber production, visual qualities, water quality and quantity, wildlife habitat, forest health, and ecology. (Twery et al. 2005)

GISCAME supports the simulation, visualisation, and evaluation of land use changes. Due to its modular structure, problems can be elaborated individually from different perspectives. It pursues the aim to evaluate land use based on available regional knowledge (empirical data, model results/reports, and expert knowledge) in order to provide a tool to weigh action alternatives for the planner. GISCAME considers the landscape as an integrative layer for interactions between different land use types, land users, and ecosystem processes, which contribute to the provision of ecosystem services. The integrated evaluation and regulation system allows the formulation of parameters as well as the setting of conversion rules. GISCAME is one of three components of the GISCAME Suite. For bundling data and for selecting a model region from an interactive map, the software OSM4GISCAME is used. Data which contain gaps or which have too low thematic resolution, can be completed or specified with the help pf the structure generator SG4GISCAME. GISCAME is based on three methodological approaches: cellular automaton (modified), geographic information system and multi-criteria evaluation. Among the areas of application belong: visualisation of impacts on land use planning alternatives, support of spatial explicit decisions, simulation of alternative planning scenarios, identification of conflict areas, tool for building compromises, e-learning instrument, evaluation of planning instruments, ecological site classification. (GISCAME 2020)

2.13.4.3 Assessment of relevant tools

A summary assessment of tools used for calculating biodiversity or for ecological site classification is provided in appendix 5.8 (Table 55).

2.14 M63: Models for the development of forest and landscape management

2.14.1 Introduction

The management of forest and landscape is a complex issue for government and private landowners due to the fact that forest projects are usually extensive. The monitoring process demands a high financial investment to guarantee legal compliance.

Forestry is concerned with applying standardized management schemes to meet management goals and serve the interests of various actors. As a consequence of differences in actors' power to influence forest management, certain goals and silvicultural ideals will be promoted at the expense of others and thereby homogenize forest management. At the same time, "ideal" outcomes are often hard to achieve in practice and forest owners might not be willing to fully implement programs promoted by the state or industrial actors due to conflicting ideas (Lodin and Brukas 2021).

However, traditional log production focuses on reduced cost and maximum revenue, which is disconnected from the landscape's sustainable use context (Ewald, 2001). From the other end of this practice, society are looking for ecologically sustainable products and, as a consequence, forest managers are planning to consider multi-objective criteria (Bettinger and Sessions, 2003; Baskent and Keles, 2005), such as water pollution (Hughes and Quinn, 2019), soil erosion and losses (Fulton and West, 2002), biodiversity (Carnus et al., 2006), connectivity among forest reserves (Augustynczik et al., 2018), socio-ecological aspects (Fischer, 2018), recreational spaces, and the aesthetic aspect value of the landscape (Panagopoulos, 2009).

For forest sustainability assessment and land use planning, landscape approaches are considered to be more and more relevant (Gardner et al. 2009). For the most part, the management unit level is only partially informative when evaluating ecosystem services and ecosystem processes that can be affected on a larger scale (Thompson et al. 2014); therefore, there is a need for tools that can cope with landscape heterogeneity and varied forest management. The temporal succession of wood harvesting from one stand to another in a highly fragmented (Živojinović 2015) forest landscape generates heterogeneity in ages and structure that cannot be easily extrapolated from the observation of a single stand. These temporal dynamics can affect a large set of parameters, from the wood production per year (affecting market and industry) to the biodiversity of these landscapes. In addition, sustainability monitoring requires a large set of indicators (FOREST EUROPE 2015) which comprise economic, social and ecological components. Tools exist to monitor these factors at a stand level, but many of them, such as Shannon diversity (Duelli and Obrist 2003), recreation (Pukkala et al. 1995) or the employment index (Orazio et al. 2006) make sense only when large areas are taken into account. These considerations lead to the development of a land use planning concertation process and an increasing demand for landscape foresight studies. Because forest is a significant part of forest landscapes in many regions, the selection of the most appropriate tools to model the evolution of various landscape parameters associated to forests over time, under many types of constraints, is highly relevant.

The landscape modelling and optimization are promising areas of research (Kaya et al., 2016) and can lead to better production in the timber industry (Liu and Lin, 2015), considering stand spatial arrangement. In this sense, selecting species or clones within the site provides improvements in forest management efficiency (Fischer et al., 2019). The monodominance of a single species or clone is undesirable more due to its lower resistance to diseases, often in the form of homogeneous mosaics (Martins et al., 2017).

An overview of existing methods, models and tools is provided, which are used for the development of forest and landscape management. The literature sources include scientific publications registered in the following databases: Scopus, Science Direct, Web of Science, Springer Link, and Science Open databases. The multiple keywords were used to find the most relevant literature sources. The documents were identified with advanced search query strings such as “(Decision making OR Optimisation OR Optimization) AND (Landscape management OR Landscape planning) AND (Forest Management OR Spatial forest planning OR Forest planning OR Forestry) AND (Method OR Model OR Tool OR System) AND (Mathematical model OR Modeling OR Modelling OR Simulation)”. The different keywords used were based on the various subjects that characterize the main research topic.

2.14.2 Relevant models

2.14.2.1 Overview of relevant models

Table 27 provides an overview of models that can be used for the development of forest and landscape management.

Table 27: Overview of models for the development of forest and landscape management.

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities / Restrictions of the Model	Implemented in S/W Products or Tools
M63.1	Heuristic	Mathematical	C	Approach to problem solving or self-discovery that employs a practical method that is not guaranteed to be optimal, perfect, or rational, but is nevertheless sufficient for reaching an immediate, short-term goal or approximation in a search space.	ETÇAP, Monsu, SIBYLA, SILVA 2.2
M63.2	Linear programming	Mathematical	C	Method to achieve the best outcome (such as maximum profit or lowest cost) in a mathematical model whose requirements are	Agflor, FMPP, MELA

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities / Restrictions of the Model	Implemented in S/W Products or Tools
				represented by linear relationships.	
M63.3	Multicriteria decision analysis	Semi-empirical	C	Evaluates multiple conflicting criteria in decision making. MCDA process can be time-consuming and demanding. Actors are not equally active during to MCDA.	EMDS, NetWeaver
M63.4	Integer programming	Mathematical	C	Mathematical optimization or feasibility program in which some or all of the variables are restricted to be integers.	
M63.5	Interpolation	Mathematical	C	Method of constructing (finding) new data points based on the range of a discrete set of known data points.	
M63.6	Dynamic programming	Mathematical, algorithmic	C	Allows simplifying a complicated problem by breaking it down into simpler sub-problems in a recursive manner.	
M63.7	Data mining	Semi-empirical	C	Process of extracting and discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems.	
M63.8	Monte Carlo method	Mathematical	C	Computational algorithms that rely on repeated random sampling to obtain numerical results. Used to solve any problem having a probabilistic interpretation.	SIBYLA
M63.9	Bayesian method	Mathematical, statistical	C	Bayesian approach permits the use of objective data or subjective opinion in specifying a prior distribution. With the	

Model Code	Model Name or Title	Nature of Model	Model Applicability in Phases	Capabilities / Restrictions of the Model	Implemented in S/W Products or Tools
				Bayesian approach, different individuals might specify different prior distributions.	
M63.10	Non-linear optimization method	Mathematical, logical	C	Allows solving an optimization problem where some of the constraints or the objective function are nonlinear.	
M63.11	Artificial Neural Networks	Semi-empirical, mathematical	C	Have the ability to acquire and maintain information based knowledge and can be defined as a set of processing units, represented by artificial neurons, interlinked by a multitude of interconnections (artificial synapses), implemented by vectors and matrices of synaptic weights	LEaRNForME
M63.12	Yield tables	Mathematical	C	Describes forest development by the system of mathematical equations.	SIBYLA, SILVA 2.2
M63.13	Growth simulator	Ecosystem and cybernetical modelling	C	It simulates different initial forest stand structures, a wide range of natural conditions defined by ecological (site) classifications in the form of climate, air, and soil characteristics, offers a quite large operating space to make the interventions of a forest manager in the form of various thinning and felling regimes.	SIBYLA, SILVA 2.2

2.14.2.2 Description of relevant models

This section presents a contextualization of the models and methods that are used in landscape and forest management and planning.

A **heuristic or heuristic technique** is any approach to problem solving or self-discovery that employs a practical method that is not guaranteed to be optimal, perfect, or rational, but is nevertheless sufficient for reaching an immediate, short-term goal or approximation in a search space. Where finding an optimal solution is impossible or impractical, heuristic methods can be used to speed up the process of finding a satisfactory solution. Heuristics can be mental shortcuts that ease the cognitive load of making a decision. (Judea 1983)

Heuristics are the strategies derived from previous experiences with similar problems. These strategies depend on using readily accessible, though loosely applicable, information to control problem solving in human beings, machines and abstract issues. (Judea 1983) When an individual applies a heuristic in practice, it generally performs as expected. However it can alternatively create systematic errors. (Cass 2005)

The most fundamental heuristic is trial and error. In mathematics, some common heuristics involve the use of visual representations, additional assumptions, forward/backward reasoning and simplification.

A heuristic can be used in artificial intelligence systems while searching a solution space. The heuristic is derived by using some function that is put into the system by the designer, or by adjusting the weight of branches based on how likely each branch is to lead to a goal node.

Heuristic methods employ logic and rules to guide the search for near-optimal results. Each have processes for releasing the search process from local optima and for both diversifying the search through less-explored areas of the solution space, and for intensifying the search around high-quality solutions. Ideally, well-designed heuristic methods would be able locate the global optimal solution to a problem; however, there are no tests of optimality to ensure this result. Further, when stochastic processes are employed in a heuristic search, one might locate a different solution with each independent run of these models, which suggests that multiple attempts for solving a problem may be necessary to provide assurance that the best result of these is near-optimal. The heuristic methods that were explored included genetic algorithms and simulated annealing. A genetic algorithm is a population-based heuristic (p-metaheuristic) that maintains a set (population) of feasible solutions (forest plans), selects a subset from the population (parents) to break apart and recombine (into children) with the goal of creating better solutions. A stochastic process (mutation) is used to prevent the population from converging upon local optima.

For stand-level management problems, a genetic algorithm would maintain several different feasible solutions to the problem in the memory of the computer and use these to create new feasible solutions to a problem through re-combination and stochastic adjustment. Genetic algorithms have been developed recently () (Niinimäki et al. 2012; Ahtisoski et al. 2012 and 2013) to optimise economic concerns at the stand level. Similar p-metaheuristics were recently demonstrated for maximisation of wood production (Pukkala et al. 2010) and forest structure (Bayat et al. 2013) at the stand-level. Constraints in most of these models were of the operational type (e.g. planting density and cutting cycle interval). Simulated annealing is a point-based heuristic (s-metaheuristic) that adjusts the condition of one feasible solution (management regime in this case) through stochastic re-scheduling of activities, with the goal of refining the solution by only allowing changes that increase (or decrease with a diminishing probability) the value of the solution. Sessions (1992) used a heuristic function for ecological corridors between wildlife areas.

Linear programming (LP), also called linear optimization, is a method to achieve the best outcome (such as maximum profit or lowest cost) in a mathematical model whose requirements are represented by linear relationships. Linear programming is a special case of mathematical programming (also known as mathematical optimization). (Sierksma and Zwols 2015)

More formally, linear programming is a technique for the optimization of a linear objective function, subject to linear equality and linear inequality constraints. Its feasible region is a convex polytope, which is a set defined as the intersection of finitely many half spaces, each of which is defined by a linear inequality. Its objective function is a real-valued affine (linear) function defined on this polyhedron. A linear programming algorithm finds a point in the polytope where this function has the smallest (or largest) value if such a point exists. (Sierksma and Zwols 2015)

Linear programming can accommodate forest management problems that have wood flow and sustainability concerns, with one of the first works applied to forestry published by Curtis (1962).

In general, there is a linear programming model to solve the forest regulation problems by defining the harvest scheduling and future management practices (Hennes et al., 1971). Therefore, the results are integrated for wood supply and silvicultural tasks. Roth (1914) reinforced the challenge faced by forest regulation not only to order the forestry work in time and space with the stands' planting or reform, but also to plan an orderly harvest, road construction, and environmental conservation. It requires an appropriate distribution of forest ages, yield, size, and wood quality (Leuschner 1990).

There are two classical models widely applied to solve the wood supply chain described by Johnson and Scheurman (1977). Type I and Type II models were used to portray the forest regulations. Both are widely used in natural resource management planning problems. A Model I linear programming problem uses decision variables that track the history of a field or stratum over the entire planning horizon, regardless of when the area will be cut. It is mostly used at the level of spatial forest planning. A Model II linear programming problem tracks the history of a field only until the final crop is examined. According to Bettinger et al. (2017), Model II is best suited for age-matched management regimes.

Multiple-criteria decision-making (MCDM) or multiple-criteria decision analysis (MCDA) is a sub-discipline of operations research that explicitly evaluates multiple conflicting criteria in decision making. Conflicting criteria are typical in evaluating options: cost or price is usually one of the main criteria, and some measure of quality is typically another criterion, easily in conflict with the cost.

MCDM is concerned with structuring and solving decision and planning problems involving multiple criteria. The purpose is to support decision-makers facing such problems. Typically, there does not exist a unique optimal solution for such problems and it is necessary to use decision-makers' preferences to differentiate between solutions.

"Solving" can be interpreted in different ways. It could correspond to choosing the "best" alternative from a set of available alternatives (where "best" can be interpreted as "the most preferred alternative" of a decision-maker). Another interpretation of "solving" could be choosing a small set of good alternatives, or grouping alternatives into different preference sets. An extreme interpretation could be to find all "efficient" or "nondominated" alternatives (which we will define shortly).

The difficulty of the problem originates from the presence of more than one criterion. There is no longer a unique optimal solution to an MCDM problem that can be obtained without incorporating preference information. The concept of an optimal solution is often replaced by the set of nondominated solutions. A solution is called nondominated if it is not possible to improve it in any criterion without sacrificing it in another. Therefore, it makes sense for the decision-maker to choose a solution from the nondominated set. Otherwise, she/he could do better in terms of some or all of the criteria, and not do worse in any of them. Generally, however, the set of nondominated solutions is too large to be presented to the decision-maker for the final choice. Hence we need tools that help the decision-maker focus on the preferred solutions (or alternatives). Normally one has to "trade-off" certain criteria for others.

MCDA process can be time-consuming and demanding. Actors are not equally active during to MCDA.

Marques et al. (2020) used MDCA to improve the evaluation of the importance of decision criteria and sub-criteria in a participatory decision on forest management in Portugal.

Integer programming problem is a mathematical optimization or feasibility program in which some or all of the variables are restricted to be integers. In many settings the term refers to integer linear programming (ILP), in which the objective function and the constraints (other than the integer constraints) are linear.

The ecological corridors for species habitats are often found in literature, and it is still a challenge for decision-makers. The main advantage of formulating habitat protection problems such as Integer Programming (IP) models with an array of objectives and constraints is site-specific policy guidance, including habitat protection activities that efficiently achieve wildlife conservation goals and trade-offs between conservation goals and protection costs (Rönnqvist et al., 2015). Nevertheless, most landscape optimization problems consider the harvest scheduling problem at the tactical level (Könnyu and Tóth, 2013; Tóth et al., 2013). Although IP is relevant for habitat maintenance and development, tactical planning is still widely used. Tactical planning is, in fact, the planning level where these types of problems are recognized.

There are two different approaches to mathematically managing the size of harvest units within a harvest scheduling model, the Unit Restriction Model (URM), which restricts the cutting of adjacent harvest units in the same period, and the Area Restriction Model (ARM), in which the adjacency restriction is controlled by maximum harvest opening sizes (Baskent and Keles 2005). These two different approaches are for handling clear-cut adjacency constraints within a mathematical programming system. That is, it seeks to ensure that the maximum predetermined cut size is not exceeded. These restrictions prevent large contiguous cutting areas from being formed (Kurttila, 2001). URM and ARM were proposed by Murray (1999), who presented a formulation of Integer Linear Programming (ILP) for URM and considered heuristic and dynamic programming to solve ARM. The ARM proposal is the same as the URM, except for expanding the cutting area in the landscape in the neighbouring units. They are two models for solving crop planning problems with spatial landscape restrictions. There are still some computational obstacles to the effective use of exact methods for these problems.

If some decision variables are not discrete, the problem is known as a mixed-integer programming problem.

Mixed-integer linear programming (MILP) involves problems in which only some of the variables are constrained to be integers, while other variables are allowed to be non-integers.

Önal and Briers (2006) formulated a mixed-integer linear programming model for establishing spatial connections between forested areas. Könnyű et al. (2015) applied a similar study to guarantee temporal connectivity within mature forest habitats over time. Wei and Hoganson (2007) formulated mixed integer programming (MIP) to describe core area production in a forest management programming model. Augustynczik et al. (2018) developed a model to integrate ecological connection corridors by maximizing the Net Present Value (NPV).

Constantino et al. (2008) proposed a Mixed-Integer Programming Model for the Harvest Scheduling Subject to Maximum Area Restrictions with Stand-clear-cut Variables (ARMSC). The approach uses a polynomial number of variables and constraints to better obtain solutions in a short computational time.

In the mathematical field of numerical analysis, **interpolation** is a type of estimation, a method of constructing (finding) new data points based on the range of a discrete set of known data points. (Sheppard 1911; Steffensen 2006)

In engineering and science, one often has a number of data points, obtained by sampling or experimentation, which represent the values of a function for a limited number of values of the independent variable. It is often required to interpolate; that is, estimate the value of that function for an intermediate value of the independent variable.

A closely related problem is the approximation of a complicated function by a simple function. Suppose the formula for some given function is known, but too complicated to evaluate efficiently. A few data points from the original function can be interpolated to produce a simpler function which is still fairly close to the original. The resulting gain in simplicity may outweigh the loss from interpolation error and give better performance in calculation process.

Dynamic programming is both a mathematical optimization method and an algorithmic paradigm. In both contexts it refers to simplifying a complicated problem by breaking it down into simpler sub-problems in a recursive manner. While some decision problems cannot be taken apart this way, decisions that span several points in time do often break apart recursively. Likewise, in computer science, if a problem can be solved optimally by breaking it into sub-problems and then recursively finding the optimal solutions to the sub-problems, then it is said to have optimal substructure.

If sub-problems can be nested recursively inside larger problems, so that dynamic programming methods are applicable, then there is a relation between the value of the larger problem and the values of the sub-problems (Cormen et al. 2001). In the optimization literature this relationship is called the Bellman equation.

Dynamic programming involves describing a problem as a set of stages (time periods) and states (conditions within the time periods). Introduced to forestry in the 1960s (Hool 1966; Amidon and Akin 1968), during the 1970s and 1980s, this was perhaps the most prevalent method studied for stand-level forest management decisions that involve determining the optimum growing stock or rotation age of even-aged forests. Paths between initial stand conditions and final stand conditions are represented as a network described by reasonable definitions of stand states (e.g. residual basal area levels) and reasonable management actions that might be employed.

Data mining is the process of extracting and discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems. Data mining is an interdisciplinary subfield of computer science and statistics with an overall goal of extracting information (with intelligent methods) from a data set and transforming the information into a comprehensible structure for further use. (Clifton et al. 2010; Hastie et al. 2009; Han et al. 2011) Data mining is the analysis step of the "knowledge discovery in databases" process, or KDD. (Fayyad et al. 1996) Aside from the raw analysis step, it also involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The actual data mining task is the semi-automatic or automatic analysis of large quantities of data to extract previously unknown, interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection), and dependencies (association rule mining, sequential pattern mining). This usually involves using database techniques such as spatial indices. These patterns can then be seen as a kind of summary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics. For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting is part of the data mining step, although they do belong to the overall KDD process as additional steps.

The difference between data analysis and data mining is that data analysis is used to test models and hypotheses on the dataset, e.g., analysing the effectiveness of a marketing campaign, regardless of the amount of data. In contrast, data mining uses machine learning and statistical models to uncover clandestine or hidden patterns in a large volume of data. (Olson 2007)

Monte Carlo methods are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to use other approaches. Monte Carlo methods are mainly used in three problem classes (Kroese et al. 2014): optimization, numerical integration, and generating draws from a probability distribution.

Monte Carlo methods can be used to solve any problem having a probabilistic interpretation. By the law of large numbers, integrals described by the expected value of some random variable can be approximated by taking the empirical mean (a.k.a. the 'sample mean') of independent samples of the variable. When the probability distribution of the variable is parameterized, mathematicians often use a Markov chain Monte Carlo (MCMC) sampler. (Hastings 1970, Liu et al. 2000) The central idea is to design a judicious Markov chain model with a prescribed stationary probability distribution. That is, in the limit, the samples being generated by the MCMC method will be samples from the desired (target) distribution.

Despite its conceptual and algorithmic simplicity, the computational cost associated with a Monte Carlo simulation can be staggeringly high. In general the method requires many samples to get a good approximation, which may incur an arbitrarily large total runtime if the processing time of a single sample is high. (Shonkwiler 2009) Although this is a severe limitation in very complex problems, the embarrassingly parallel nature of the algorithm allows this large cost to be reduced (perhaps to a feasible level) through parallel computing strategies in local processors, clusters, cloud computing, etc.

A key feature of **Bayesian methods** is the notion of a probability distribution for a population parameter. According to classical statistics, parameters are constants and cannot be represented as random variables. Bayesian proponents argue that, if a parameter value is unknown, then it makes sense to specify a probability distribution that describes the possible values for the parameter as well as their likelihood. The Bayesian approach permits the use of objective data or subjective opinion in specifying a prior distribution. With the Bayesian approach, different individuals might specify different prior distributions. Classical statisticians argue that for this reason Bayesian methods suffer from a lack of objectivity. Bayesian proponents argue that the classical methods of statistical inference have built-in subjectivity (through the choice of a sampling plan) and that the advantage of the Bayesian approach is that the subjectivity is made explicit. (Howson 2001)

Bayesian methods have been used extensively in statistical decision theory. In this context, Bayes's theorem provides a mechanism for combining a prior probability distribution for the states of nature with sample information to provide a revised (posterior) probability distribution about the states of nature. These posterior probabilities are then used to make better decisions.

Regression analysis as one of the traditional methods has been applied in the model generation (Chopra et al. 2014; Nuruddin et al. 2015). **Multiple regression (MLR) analysis** is a statistical technique to determine the relationship between independent and dependent variables. The accuracy of regression models increases considerably by using MLR while it decreases when the independent variables increase (Chopra et al. 2014). In these complex cases, nonlinear and dynamic modelling techniques like **artificial neural networks (ANN)** are employed for the development of accurate complex probabilistic models (Intharathirat et al. 2015).

ANNs have the ability to acquire and maintain information based knowledge and can be defined as a set of processing units, represented by artificial neurons, interlinked by a multitude of interconnections (artificial synapses), implemented by vectors and matrices of synaptic weights (da Silva et al. 2017). The ANN model can be applied to various kinds of problems, from classification, clustering and optimisation to function approximation, and has already been applied in various forestry disciplines, such as forest fire prediction (Safi and Bouroumi 2013), prediction of insect outbreaks (Park and Chung 2006), and species distribution models (Scrinzi et al. 2007). Apart from these, the ANN has also been tested in tree height modelling for eucalyptus trees (Vieira et al. 2018), common beech (Fagus sylvatica) from northwestern Spain (Castaño-Santamaría et al. 2013) and Crimean juniper (Juniperus excels) (Özçelik et al. 2013).

Jahani (2019) aimed at developing artificial neural network (ANN) modelling and multiple regression (MLR) analysis approaches to predict the perception aesthetic quality of forest landscapes. Today, the landscape aesthetic quality assessment is more technical and quantitative in environmental management. The methodology can be divided into six distinct parts: 1) selection of representative study sites, 2) mapping of landscape units, 3) quantification of naturalness indicators, 4) visibility analysis, 5) assessment of human perceptions, 6) ANN and MLR modelling and sensitivity analysis. The results of ANN modelling, especially its high accuracy (R^2 = 0.871) in comparison with MLR results (R^2 = 0.782), introduced the forest landscape aesthetic quality model (FLAQM) as a comparative model for an assessment of forest landscape aesthetic quality. According to sensitivity analysis, the values of livestock density, tree harvesting, virgin forest, animal grazing, and tree richness were identified as the most significant variables which influence FLAQM. FLAQM can be used to compare the classes of aesthetic quality of forests.

Nonlinear programming (NLP) is the process of solving an optimization problem where some of the constraints or the objective function are nonlinear. An optimization problem is one of calculation of the extrema (maxima, minima or stationary points) of an objective function over a set of unknown real variables and conditional to the satisfaction of a system of equalities and inequalities, collectively termed constraints. It is the sub-field of mathematical optimization that deals with problems that are not linear. (Luenberger and Ye 2008)

Spatial forest planning is causally related to **geovisualization** and the processing of geographic data. Spatial forest planning using meta-heuristic techniques, associated with Spatial Decision Support Systems (SDSS) and developed in multiple programming languages, should be explored. In the microplanning and optimization of stands, an important current challenge for forestry companies is to achieve greater homogeneity in their stands.

In 1996, with the possibility of using ESRI Shapefiles (Environmental Systems Research Institute) in forestry decision support systems with resources for spatial planning, the Canadian company Remsoft Inc. launched the Stanley software (Spatial Optimizer), which uses sets of heuristics for the automatic insertion of spatial constraints in strategic forest-planning models with multi-objective linear programming (Goals programming). It was an important step in dealing with the inclusion of new sustainability criteria in forest management planning. Heuristics-based shapefiles applying the imposition of adjacent and green-up constraints on spatial parameters help the planner to better control the minimum, average, and maximum size of the cutting units and the green-up period between adjacent areas. (Cavalcante de Jesus França et al. 2022)

Therefore, statistical or mathematical models and geospatial support of SDSS provide forest landscape management more comprehensively, creating an effective link between strategic and operational levels.

Yield tables represent a mathematical model, which today describes forest development by a system of mathematical equations. It simulates the development of even-aged homogeneous forest stands (pure plantations) at full density and 100% proportion of a particular tree species in relation to age and site. The site is defined by stand class, or also by stand volume level. Yield tables are restricted to only one thinning regime, or eventually to a set of pre-defined variant regimes with no possibility to modify them. The outputs are primarily oriented at production aspect of a forest, while usually they are presented in tabular form. Due to the model simplicity and to the restricted range of possible variants of a forest, the model does not have to exist as a computer program. It is mainly composed of simple growth curves, or eventually of other mensuration relationships. The model is strictly deterministic, and hence, its character is often normative. Due to the facts that this model does not require many input parameters and is simply applicable, it is primarily used in the forestry practice. (TUZVO 2023)

A growth simulator is a system that strives to imitate forest behaviour using the principles of ecosystem and cybernetical modelling. It utilises a very wide range of input conditions and parameters. It simulates different initial forest stand structures starting from even-aged homogeneous stands (pure plantations) of the type of age classes, through differentiated multi-storeyed forest, mixed stands and shelterwood systems, up to selection forests. It is able to simulate a wide range of natural conditions defined by ecological (site) classifications in the form of climate, air, and soil characteristics. In addition, it also offers a quite large operating space to make the interventions of a forest manager in the form of various thinning and felling regimes. And besides, a specific economic environment is accounted for inclusive of applied technological techniques. At the same time, growth simulator provides a user with a great variety of output data. Apart from classical production data it also deals with ecological information, such as biodiversity, biomass, fixation of nutrient elements in trees, oxygen production and carbon dioxide consumption. It also covers an economic aspect in the form of assortment structure of produced wood, forest revenues and management costs. To imitate the real forest as faithfully as possible, stochastic principles are applied, i.e.

every time the simulation is repeated, the model produces slightly different results. The behaviour of randomness follows the probability principles and functions derived from real forest ecosystems. Thanks to the randomness, the component of theoretical model error can be obtained, and statistical tests of the differences between various scenarios can be performed. The nature of the system is complex, since it utilises a set of various linked models and algorithms of a different nature: allometric equations, regressions, growth curves, mensuration relationships, physical and chemical relationships, production rules, Boolean and fuzzy logic, heuristics, planar and spatial geometry, two- and multi-dimensional probability models, etc. Due to this complexity, it is undoubtedly required that the system exists in the form of a computer program. Since the system is characterised by a number of input parameters and a variety of possibilities to define different variants and scenarios, its application is more challenging. Primarily, it is suitable for scientific and educational purposes. (TUZVO 2023)

2.14.2.3 Assessment of relevant models

A summary assessment of models that can be used for the development of forest and landscape management is provided in appendix 5.9 (Table 56).

2.14.3 Relevant tools

2.14.3.1 Overview of relevant tools

Table 28 provides an overview of tools that can be used for the development of forest and landscape management.

Table 28: Assessment of tools that can be used for the development of forest and landscape management.

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
T63.1	AFFOREST-sDSS	Windows, ArcGIS	C	afforestation management, carbon sequestration, ecological classification, groundwater recharge, nitrate leaching, species selection, water quality	Supports tree species spruce, pine, oak or beech
T63.2	Agflor	Windows	C	afforestation management, economic evaluation, agroforestry	the model does not specifies any tree species in particular and thus is applicable for variety of tree species.
T63.3	AVVIRK-2000	Windows	C	biodiversity evaluation, landscape quality, yield prediction, wood supply planning	Supports tree species Norway spruce (Picea abies), Scots pine (Pinus sylvestris), birch (Betula spp.)

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
T63.4	Capsis	Linux / Windows / Mac Os X	C	forestry growth and yield / dynamics models	Not specified
T63.5	ClimChAlp	Linux/Unix	C	afforestation management, carbon sequestration, climate change impact, ecological classification, economic evaluation, forest health, groundwater recharge, silvicultural regime, species selection, wind hazard, multi-functional	Supports tree species Norway Spruce
T63.6	CONES	Windows	C	silvicultural regime, species selection, multi-functional	Supports tree species: Norway Spruce, Europ. Larch, Scots Pine, Silver Fir, Europ. Beech, Maple, Birch, Sycamore
T63.7	DSD	Not specified	C	forest health, species selection, multi-functional	Supports tree species: Norway Spruce, White Pine, Oak, Maple
T63.8	EFIMOD	Windows	C	assessment of carbon sequestration, climate change and natural disturbances, soil dynamics and wood production under different regimes of forest management	Supports tree species as Spruce, Pine, Birch, Aspen, Lime, Oak; other species can be included after additional parameterization
T63.9	EFISCEN	Windows	C	biodiversity evaluation, biomass estimation, carbon sequestration, climate change impact, forest inventory, yield prediction, wood supply planning	Not specified
T63.10	EMDS	Windows, ArcGIS	C	multi-functional, user defined	Not specified
T63.11	ETÇAP	Windows	C	Harvest scheduling, timber production, yield prediction,biodiversity	Not specified

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				conservation, landscape quality	
T63.12	FMPP	Windows	C	afforestation management, economic evaluation, forest inventory, silvicultural regime, wood supply planning	Supports tree species: Norway spruce; Scots pine; Birch; Oak; Beech; Other deciduos
T63.13	ForestGales	Windows	C	storm behaviour, wind hazard	Supports tree species: Sitka Spruce, Norway Spruce, Douglas Fir, Scots Pine, Corsican Pine, Lodgepole Pine, Western Red Cedar, Western Hemlock, Noble Fir, Grand Fir, Japanese Larch, Hybrid Larch, European Larch
T63.14	FORFUN	Windows	C	multi-functional tool	
T63.15	FVS	Windows	C	biomass estimation, carbon sequestration, climate change impact, fire behaviour, forest fuel harvesting, forest vegetation management, silvicultural regime	Any number of projection units (stands) can be processed in a simulation. There is a limit of 500 plots or points in any projection unit. There is a limit of 40 time period 'cycles' for any simulation, but the length of the cycles can be controlled by the user.
T63.16	Heureka PlanWise	Windows	C	multi-functional	Not specified
T63.17	LANDIS II	Windows	C	forest ecology, forest health, forest vegetation management, silvicultural regime	Not specified
T63.18	Landscape DSS	Windows	C	Biodiversity (including ecological fire groups, Wet forest, ecological refuges, Leadbeater	Not specified

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				possums and Greater Gliders) Carbon Experienced High Conservation Values Infrastructure loss (e.g., roads, powerlines, industrial building, hospitals) People and House loss Geometric Mean of Species Abundance Shannon's diversity and Fractal dimension index Soil Erosion Rates Major Water Contamination Events Visual aesthetics viewshed,	
T63.19	LEaRNForME	Linux/Unix, Windows	C	multi-functional, shallow landslides, water erosion and runoff generation; vegetation cover functionality	Supports tree species: all the Italian forest types
T63.20	MELA	Windows	C	biomass estimation, carbon sequestration, economic evaluation, yield prediction, wood supply planning	Supports tree species: Scotch pine (Pinus sylvestris), Norway spruce (Picea abies), Silver birch (Betula pendula), Downy birch (Betula pubescens), Aspen (Populus tremula), Alder (Alnus incana, Alnus glutinosa), Other coniferous species, other deciduous species
T63.21	Mesta	Web-based	C	multi-functional	Not specified
T63.22	Monsu	Windows	C	biomass estimation, carbon sequestration, economic evaluation, forest fuel harvesting, silvicultural regime, yield prediction, wood	Inventoried field data are required. Furthermore, not only living trees must be inventoried, also dead trees,

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				supply planning, user defined	because they are considered important for biodiversity.
T63.23	NED-2	Windows, ArcGIS	C	biodiversity evaluation, conservation, ecological classification, economic evaluation, groundwater recharge, landscape quality, natural hazards, water quality, wildlife habitat, wood supply planning, hunting, multi-functional	Not specified
T63.24	ProgettoBosco	Windows	C	forest vegetation management, silvicultural regime, multi-functional	facilitates links to GIS
T63.25	GISCAME	Not specified	C	biodiversity evaluation, biomass estimation, carbon sequestration, climate change impact, conservation, ecological classification, economic evaluation, landscape quality, non-wood production, soil erosion, water quality, wildlife habitat, wood supply planning, multi-functional, user defined	oriented on forest types, not for specific species
T63.26	SADfLOR web-based	Web-based	C	biomass estimation, carbon sequestration, climate change impact, economic evaluation, silvicultural regime, species selection, yield prediction, wood supply planning	Supports tree species: Eucalyptus, Maritime pine, Stone pine
T63.27	SIBYLA	Windows	C	generator of forest stand structure, 3D visualization of a simulation plot, inter-tree competition, growth simulator, natural tree mortality, simulation of dying of	freeware if it is to be used for non-commercial activities

Tool Code	Tool Name or Title	Install ability	Tool Applicability in Phases	Capabilities of the Model	Restrictions of the Model
				trees, thinning and felling treatments	
T63.28	SILVA 2.2	Windows	C	a single-tree-based, position-dependent simulation model, thinning model	SILVA does not command an automatic optimization algorithm. Optima are usually approximated manually by sensibly defining and modifying scenario settings

2.14.3.2 Description of relevant tools

AFFOREST-sDSS deals with environmental performance of afforestation on agricultural land in northwestern Europe. The environmental performance of afforestation on agricultural land is defined in terms of three parameters: (1) Carbon sequestration, (2) Groundwater recharge, and (3) Nitrate leaching. It is supranational project, developed in partnership by researchers from Flanders (Belgium),the Netherlands, Denmark and Sweden. AFFOREST-sDSS uses the metamodel METAFORE to compute the environmental performance for each initial system in the study area with the data provided by the AFFOREST spatial database. Decisions supported by AFFOREST sDSS are the selection of sites and the specification of afforestation practices and management, with a view to optimize one or more of the three studied environmental impact categories: carbon sequestration in the ecosystem including biomass and soil, groundwater recharge, and nitrate leaching to deeper soil layers and groundwater bodies. (Gilliams et al. 2005)

Agro-forestry decision support system (**Agflor)** is a tool to help access the impacts of policy changes on regional land use patterns. It was used by Portuguese Ministry of Agriculture Regional Office of Alentejo (DRAPAL) to assess the impacts of common agricultural policy changes on agricultural and forestry activities on regional land use patterns over an area extending over 2 million hectares. (Borges et al. 2010)

AGfLOR uses a linear programming model and a simulated annealing meta-heuristic. A Positive Mathematical Programming model is used to calibrate mathematical programming models according to observed behaviors during a reference period. It aims to assess economic, technical and institutional scenarios associated with changes in policies, relative prices, technologies and availability of inputs.

AVVIRK-2000 is a deterministic simulation model, with no elements of optimization or stochasticity built in. The simulation system comprises two phases: 1) Simulations are made for each individual stand, and 2) the potential harvest at the forest level (i.e. the union of all stands) is calculated. In this second phase, in case of existence of harvest constraints an iterative tool operating heuristics should be used, in order to achieve a few, but satisfactory solutions. Harvest constraints allowed are: a non-declining harvest path or net income path for the period of 100 years, a user-given harvest level or net income level for any number of 10-year periods up to 10, a harvest path according to user-given final harvest ages for all stands, or a harvest path according to removal of stands with relative annual value increment lower than a user-given percentage. Until now, the model has only taken into account timber production considerations. It provides harvest scheduling and consequence analyses, practical management planning for analyzing harvests at forest level by companies. AVVIRK-2000 uses a deterministic simulation model with no elements of optimization or stochasticity built in. (Eid and Hobbelstad 2000)

Capsis is a software platform which purpose is to host forestry growth and yield / dynamics models. It can help run various silvicultural scenarios by combining a given growth model with silvicultural treatments. It was built by French researchers (INRA, France) for forest research (hypotheses testing, model evaluation), transfer to forest managers (particularly French) and educational purposes. It makes possible to implement models of various types (stand models, distance-independent or distance-dependent tree models, mixt models…), to run simulations and then compare the different scenarios in the same tool. According to its flexible architecture, it is possible to integrate heterogeneous models (uneven-aged, several species) with various processes (growth, competition, mortality, regeneration…) and to run simulations in interactive or script modes. Some models can have very particular properties, e.g. radiative balance, genetics information at the individual level, internal biomechanics or wood quality. (de Coligny 2007)

ClimChAlp is a web-based decision support system to explore adaptation options for silviculture in secondary Norway spruce forests in Austria. ClimChAlp focuses on the question of suitable stand treatment programmes for currently existing Norway spruce stands given a particular set of management objectives (represented by a set of indicators focusing on timber production, ecophysiological tree suitability, timber yield, harvesting and silvicultural costs, carbon sequestration, biodiversity and groundwater recharge). The tool is particularly designed to support the consultation process of the forestry extension services for small-scale private landowners. The staff of the forestry extension services has a key role in knowledge transfer to small scale owners who often do not have any professional background in forestry. Therefore, the DSS was supposed to (a) inform the extension foresters about potential impacts of climate change on Norway spruce forests and provide them with information on alternative stand treatment options; and (b) to assist them by various means of visualization to support the consultation session. (Vacik et al. 2010)

CONES is a practicable and easy to use spatial decision support system (SDSS) for the people involved in the decision making process at the ÖBf-AG in Austria. It allows the user to evaluate different treatment alternatives as a combination of harvest and forest regeneration strategies in order to select the pareto-optimal solution for a given situation. The decision support tool is implemented using the software package ArcGIS. Among the output data formats belongs table, graph, map, and pre-programmed summaries. A full simulation run for hundred years with several management prescriptions might take between 2-5 min. (Palmetzhofer et al. 2004)

Decision Support Dobrova (DSD) was developed by a research team at the University of Natural Resources and Life Sciences, Vienna (Universität für Bodenkultur Wien) for providing support for extension services by the local forest administration in Carinthia (southern Austria). The first prototype was implemented in 2001. DSD supports two main silvicultural decision-making problems, both for individual stands: 1. The establishment of new stands. It seeks which species or species mixtures are suitable at particular locations within the project area, including considerations of the effect of climate change. 2. Stand treatments scheduling, given a particular set of management objectives aiming at a future species-mixture stand type. DSD was designed to include five components: GUI, database, reporting and documentation, Help/Hypertext, scenario manager. (Lexer at al. 2005)

EFIMOD-Discrete Lattice Ecosystem Simulator is a tool to forecast carbon and nitrogen flows in forest ecosystems with strong feedback mechanism between soil and stand. It allows for description and spatial analysis of mixed stand dynamics in boreal and temperate forests at different management and external impacts. The system is designed to take into account timber harvest effects, dynamics of ecosystem and forest understory biodiversity, climate change effects, landscape analysis methods, nitrogen deposition effects, and fires. (Komarov et al. 2003)

The modelling tool of forest ecosystem EFIMOD (Chertov et al. 1999; Komarov et al. 2003 and 2007) is an individual-based spatially explicit simulator of tree-soil system that calculates parameters of carbon balance and standard forest inventory characteristics: NPP, Rh, soil available nitrogen, tree and stand biomass by tree compartments, soil organic matter (SOM) and N pools, stand density, height, DBH, growing stock and some other parameters. It includes soil model ROMUL as an important component that is driven by soil water, temperature and SOM parameters. The statistical generator of soil climate SCLISS was compiled to run ROMUL. The EFIMOD allows for a calculation the effect of silvicultural operations and forest fires. Now it is linked with a system of plant biodiversity assessment BioCalc.

The ROMUL model (Chertov and Komarov 1997; Chertov et al. 2001) of soil organic matter (SOM) and nitrogen mineralisation and humification calculates the transformation of litter and SOM compartments, the gross carbon dioxide flow from the soil due to SOM mineralisation and the nitrogen available for plant growth. The rate of litter and SOM mineralisation and humification is dependent on the litter quality, soil temperature and moisture, and on some soil parameters. The model validation and sensitivity analyses had been performed using a set of published laboratory and field experiments (Chertov and Komarov 1997; Chertov et al. 2001; Komarov et al. 2007).

A soil climate generator SCLISS (Chertov et al. 2001) is used in the model for two purposes: (1) as a method of evaluation of soil temperature and moisture using measured standard meteorological long-term data; (2) statistical simulation (generation) of realisations of long-term series of necessary input climate data with known statistical properties. The model uses monthly average data on air, litter and soil temperature, precipitation, litter and mineral soil moisture.

A model BioCalc (BIOdiversity CALCulator) forecasts dynamics of ecosystem and species understorey diversity of each forest unit along the EFIMOD simulation outputs on a base of standard forest inventory data linked with the results of detailed phytosociological research (Khanina et al. 2007).

European Forest Information Scenario Model (EFISCEN) is a large-scale forest model that projects forest resource development on regional to European scale. The model is suitable for the projection of forest resource development for a period of 50 to 60 years. The model uses national forest inventory data as a main source of input to describe the current structure and composition of European forest resources. Based on this information, the model can project the development of forest resources, based on different scenarios. These scenarios are mainly determined by management actions, but the model can also take into account changes in forest area, as well as changes in growth e.g. due to climate change. EFISCEN provides data on basic forest inventory data (species, area, stemwood volume, increment, mortality, age-structure), but the model includes multiple indicators related to important forest ecosystem services (carbon sequestration, biodiversity, recreation, wind and fire risk), enabling the assessment of impacts of different policy and management strategies at the national and European level. Through its underlying detailed forest inventory database, the projections provide these insights at varying scales, thus serving forest managers and policy makers at the national and international levels. The current version of the model is EFISCEN 4. (Verkerk et al. 2016)

Ecosystem Management Decision Support System (EMDS) provides decision support for landscape-level analyses through logic and decision engines integrated with the ArcGIS geographic information system. The NetWeaver logic engine evaluates landscape data against a formal logic specification designed in the NetWeaver Developer system, to derive logic-based interpretations of ecosystem conditions. The decision engine evaluates NetWeaver outcomes, and data related to the feasibility and efficacy of land management actions, against a decision model for prioritizing landscape features built with its development system, Criterium DecisionPlus. CDP models implement the analytical hierarchy process, the simple multi-attribute rating technique, or a combination of the two methods. The system has been used in a high variety of applications. It provides logic-based evaluation of landscape condition. Topic of analysis is defined by user. Scale of analysis is set by user. Second stage sets priorities for landscape units. MCDM for priorities is defined by user. (Reynolds and Hessburg 2014)

ETÇAP is an ecosystem based multiple use forest management planning software that allows to evaluate the current state of a forest ecosystem (forest inventory compilation, develop management strategies with a number of management objectives and constraints, projects future forest development with various

Operation Research Techniques and prepares and lays out a management plan based on management guidelines. It provides support for specific issues as harvest scheduling, timber production, yield prediction, biodiversity conservation, and landscape quality. It also provide support for specific thematic areas of a problem type: silvicultural prescription, conservation, development choices / land use zoning, policy/intervention alternatives. The simulation tool runs the different management possibilities among the restrictions imposed by the input data to understand forest dynamics. The optimization tool projects the current state of a forest into a target forest under various management prescriptions with objectives and constraints. Heuristic tools are used in order to ensure the spatial layout of the best management option chosen by the manager. Three groups of data are needed for the model; the current area of the stands generated by a GIS software, current status of each stand measured with inventory sheets for per area growth and yield characteristics (in each plot: the plot size, diameters of all stems, ages of some stems, age and dominant height for a number of stems, and ten-last-years growth for some trees) and the other support tables (volume table, empirical yield table, site index table, product assortment table and financial value table) characteristics In order to allow spatial layout of a harvest schedule for visualization and generation of maps, compartments, forest stratifications and analysis areas have to be set and related to each polygon (a sub-compartment =stand) with geographic files. (Başkent et al. 2008)

Forest Management Planning Package (FMPP) is an existing planning system used in practical forestry in Sweden. It focuses on the economically effective resource management of forest timber. The FMPP integrates economic theory, objective inventory measurements, growth forecasts and optimization methods. It is essentially aimed at long term (strategic) planning of larger forest holdings. The planning problem can be formulated and solved in two ways. (1) A non-linear objective function and mathematical optimization result in a compromise between maximization of economics benefits (Net Present Value) and a sustainable development (sustained net-revenue profile). (2) A linear programming package, JLP, is utilized to maximize Net Present Value under some preselected restrictions. Forest growth prediction models are used. Also, economic evaluation through the NPV is made. It can be used for operational and strategic planning, although it fits better to strategic planning requirements, since it has been developed toward this goal. (Jonsson et al.1993)

ForestGales allows the analysis of wind climate effects on the stability of a conifer forest. The tool can be used to assess risk over time via predicted growth from yield tables or alternatively current risk from mensuration data (top height and dbh). It evaluates the wind hazard of a conifer stand plantation, based on some of the stand feature, like soil, cultivation, drainage, location, or metric measures (top height, average dbh) of the existing species. It provides information as the return period for that damage to occur, risk status and critical wind speed for both overturning and stem breakage risk. It allows to quantify the wind hazard existing in actual stands or, with the help of growth prediction models or yield tables, the future risk of wind damage assumed by current decisions on the establishment of new plantations, drainage improvements, thinning options, clear-cutting impact, rotation periods or the creation of retentions. ForestGALES can be used to calculate the risk for a particular stand in the single stand mode, or in the batch or multiple stand mode, for a number of stands one after another. Within these two modes there are three ways of making predictions: using field measurements, using stand characteristics provided by a yield model, or making predictions through time, calculating the risk of damage over a typical rotation from stand characteristics contained in yield models. Recently adapted as part of Stormrisk project to allow model to run in partner countries. Stand based tool operates at stand scale up to 10 hectares, batch GIS tool has generated regional and national scenarios. The ForestGALES model takes into account the effect of species, cultivation, drainage and silviculture. Using information about the site (including soil and cultivation) and the trees (such as species and height), the model first calculates the wind speed at which trees will be damaged either by uprooting or stem breakage. A mechanistic model is used in order to estimate this parameter. The probability of damaging winds occurring is then calculated using information on the wind climate. (Forest Research 2023)

FORest FUNctions (FORFUN) is a computerized tool for ranking forest functions at stand scale. It is a designed to assign a score to the functions of the forest in a given forest compartment, ranking them in order of importance. To this end a multicriteria algorithm is employed using two criteria: site suitability and stand aptitude for the given functions. For each criterion and for each function a group of indicators represented as GIS layers was chosen. The two criteria can be attributed roughly the same weight as assessed by the planner. The result can be corrected with a coefficient expressing the relative importance assigned to each function by the stakeholders through questionnaires whose outcome are processed by a Saaty matrix. It computes up to hundreds of forest compartments of a single management or landscape scale forest plan. (Portoghesi et al. 2013)

Forest Vegetation Simulator (FVS) is a family of forest growth simulation models. The FVS GUI is the graphical user interface for the FVS software. Running in a web browser, FVS enables the user to read inventory data, perform simulations with and without management, and analyze the results. The basic FVS model structure has been calibrated to unique geographic areas to produce individual FVS variants. Since its initial development in 1973, it has become a system of highly integrated analytical tools. These tools are based upon a body of scientific knowledge developed from decades of natural resources research. is a model used for predicting forest stand dynamics, and is used extensively throughout the United States. FVS is the standard forest dynamics model used by various government agencies including the USDA Forest Service, USDI Bureau of Land Management, and USDI Bureau of Indian Affairs. It is also used by state agencies, industry, educational institutions, and private landowners. Forest managers have used FVS extensively to summarize current stand conditions, predict future stand conditions under various management alternatives, and update inventory statistics. Output from the model is used as input to forest planning models and many other analysis tools. In addition, FVS has been linked to other Forest Service corporate software such as databases and geographic information systems. Uses of FVS are not restricted to timber management applications. Other uses of FVS include considering how management practices affect stand structure and composition, determining suitability of stands for wildlife habitat, estimating hazard ratings for insect outbreaks or wildfires, and predicting losses from fire and insect outbreaks. The typical projection unit in FVS is a stand, but the size of the projection unit is not limited. Many stands may be included in a simulation, alllowing analysis at the level of the smallest project, such as a thinning on several acres, all the way up to the watershed and landscape level, such as a national forest plan. The entire FVS system is a collection of models. There are separate models for things like tree growth, mortality, regeneration, understory vegetation, fire, fuels, wood volumes, carbon, biomass, insects, diseases, and economics. A model to simulate the effects of climate change is also in development. Things like habitat suitability and risk to a particular pest can be easily calculated or inferred from the FVS outputs. Any number of projection units (stands) can be processed in a simulation. The FVS software system is comprised of the FVS geographic variants, model extensions, and a graphical user interface. There is a limit of 500 plots or points in any projection unit. There is a limit of 40 time period 'cycles' for any simulation, but the length of the cycles can be controlled by the user. (US Forest Service 2023)

Heureka PlanWise is a system for long and medium term forestry planning and scenario analysis. It consists of several applications: (1) StandWise for stand-level management analysis, (2) PlanWise for forest-level planning, (3) RegWise for regional scenario analysis, (4) PlanEval for multi-criteria deciion analysis to rank plans created in PlanWise and RegWise with one pr more stakeholders, and (5) Habitat Prognosis, a AcGIS-based application for habitat suitability analysis of a given plan. The system covers the whole decision support process from data inventory to tools for selecting among plan alternatives with multi-criteria decision making techniques. The system is designed for both large-scale and small-scale forestry. The utilities handled today are timber and bio-fuel production, carbon sequestration, biodiversity, and recreation. (Wikström et al. 2011)

LANDIS-II forest landscape model simulates forests (both trees and shrubs) at decadal to multi-century time scales and spatial scales spanning hundreds to millions of hectares. The model simulates change as a function of growth and succession and, optionally, as they are influenced by range of disturbances (e.g., fire, wind, insects), forest management, land use change. Climate and climate change affect processes throughout the model. LANDIS-II is highly customizable with dozens of libraries ('extensions') to choose from. Completely open-source with extensive documentation. (Scheller et al. 2007)

Landscape DSS assists land managers and communities to explore potential changes in multiple landscape values associated with fire regimes, changing climate, and alternative management practices. is a prototype knowledge and evaluation system that, when fully developed will assist land managers and communities to explore potential changes in multiple landscape values associated with fire regimes, changing climate, and alternative management practices. This DSS utilizes two models to assess changes in landscape values – the fire regime simulator FROST and the forest landscape vegetation dynamics model LANDIS-II. Each year FROST first simulates fire in the landscape in response to particular climate, suppression, and prescribed burning inputs. LANDIS-II then simulates changes in forest structure and composition over time in response to this fire and LANDIS-II modelled harvesting (i.e. it enacts vegetation mortality, regeneration, and growth), and then feeds this vegetation information back into FROST for a successive fire year. These yearly FROST and LANDIS-II outputs are also fed into FRAPPE (part of the FROST Family software). FRAPPE uses modelled algorithm(s) to analyse how these outputs impact different landscape values of interest. These landscape values include: Biodiversity (including ecological fire groups, Wet forest, ecological refuges, Leadbeater possums and Greater Gliders); Carbon; Experienced High Conservation Values; Infrastructure loss (e.g., roads, powerlines, industrial building, hospitals); People and House loss; Geometric Mean of Species Abundance; Shannon's diversity and Fractal dimension index; Soil Erosion Rates; Major Water Contamination Events; Visual aesthetics viewshed. In this way, the DSS brings together fire regimes and landscape vegetation changes to explore how changes in future climate and management practices may impact on important landscape values. (FLARE Wildfire Research 2023)

LEaRNForME is an instrument for the land planning able to recognize the role of the vegetation cover in controlling some hydro geological instability phenomena. This evaluation provides the opportunity to introduce environmental issues into forest planning. A procedure has been conceived and implemented in order to support the forester in classifying each homogeneous land unit for: predisposition to instability phenomena (termed "propensity") such as shallow landslides, water erosion and runoff generation; vegetation cover functionality in contrasting these events. Both aspects have to be described and modelled by means of distinctive sets of variables; neural network analysis is then applied to a comprehensive set of study cases. The resulting evaluations of predisposition and functionality are combined into four different indexes with descriptive and planning significance: equilibrium level, a rough estimation of the balance between tendency and cover protection; protection value, assessment of the ability of the vegetation in controlling land degradation; constraint level, grade of limitation with respect to timber-oriented management compatible with the assessed protection value; action priority, preliminary screening of land units requiring ameliorative practices. At present only the models devoted to the protection from shallow landslides and soil water erosion are operating. The user provides basic input data about the site conditions (lithology, aspect, slope, vegetation cover, erodibility, land use, practices, disturbances, etc.). In the shallow landslides model, the users input data to evaluate propensity to instability phenomena concerning: lithology, strata bedding, aspect, slope, climatic aggressiveness, drained area and seismicity. To evaluate vegetation cover protective functionality, the user input data about category of vegetation types, vegetation types, dominating vegetation cover, cover gaps, secondary vegetation cover, forest management disturbances, other disturbances, forest engineering practices, forest engineering practices. In the soil water erosion model the user input data to evaluate the propensity to instability phenomena concerning erodibility, climatic aggressiveness, heat load index, topographic factor. To evaluate vegetation cover protective functionality, the user input data concerning land use categories, land use, dominating vegetational cover, bushes cover, grasses cover, dead materials cover, agro-forest management disturbances, practices, slope. The system use Artificial Neural Network (ANN) models. (Andrenelli et al. 2007)

MELA is an operational decision support system developed and maintained by Metla (Finnish Forest Research Institute) based on its forest research. This system has been used since the 1980s in the analyses of wood production possibilities and the impact of different harvest levels at national and regional scale in Finnland. It is a general analysis tool for forest management planning. It can be used e.g. in the computational updating of forest resource data and in the search of effective or optimal production programs for forest areas (a property or a company). When linked with end-user applications for forest planning, the MELA software supports interactive planning. For example, the current MELA version provides more diversified and detailed information for taking into account errors and risk. Furthermore, MELA allows flexible combinations of various data sources and models to improve cost-efficiency and effectiveness of forest inventory and planning. It consists of two separate programs communicating with each other's via MELA system files: MELASIM (an automated stand simulator based on individual trees) and MELAOPT (optimization package based on the linear programming package, JLP). (Redsven et al. 2007)

Mesta is an internet-based decision-support application for (participatory) maker strategic-level natural resources discrete choice situations. It has been designed to support multi-criteria decision making situations. It demands the decision maker to define his/her acceptance threshold (=border of approval) for all predefined criteria. The acceptance border definitions are continued until only one alternative exists that is above the acceptance borders. On the other hand, the functioning reminds approval voting. On the other hand, the functioning reminds feasible region reduction method. However, in Mesta, the alternatives and their criteria values have been created before the approval border definitions. It is a general system and it can be applied to numerous decision situations (buying a car, selecting a treatment schedule for stand, and selecting a strategy for a region etc.). (Kangas et al. 2008)

Monsu is a calculation and planning software that was developed in Finland in order to be used within multiple-use forestry. It covers scheduling plans generation, numerical optimization and results graphical visualization. Monsu forest management planning follows three steps [1]:

Management scheduling: The forest under planning is divided into compartments, and each compartment is inventoried in the field. The field data (from both living and dead trees are imported to a compartment database. Then, alternative treatment schedules are simulated for the stand compartments. Each treatment schedule is described by treatments attached to it, timber removals, and development of the growing stock characteristics. (Pukkala 2004)

Planning model: it has a planning model writer and various optimisers. The first combines information on decision maker's objectives, and production possibilities of the before simulated treatment schedules of stands. The optimizer can use linear programming and goal programming models, as well as utility theoretic problem formulations, solved with heuristics.

Solution presentation: it includes a visual interface and a landscape visualizer to interactive optimization and also useable after it. (Pukkala 2004)

It provides support for specific thematic areas of a problem type: silvicultural, certification, conservation, development choices / land use zoning, policy/intervention alternatives. Heuristic tools are used in order to ensure the best management option is the chosen one by the manager. (Pukkala 2004)

NED-2 is a Windows-based system designed to improve project-level planning and decision making by providing useful and scientifically sound information to natural resource managers. Resources currently addressed include visual quality, ecology, forest health, timber, water, and wildlife. NED-2 expands on previous versions of NED applications by integrating treatment prescriptions, growth stimulation, and alternative comparisons with evaluations of multiple resources across a management unit. The NED-2 system is adaptable for small private holdings, large public properties, or cooperative management acros multiple ownerships. NED-2 implements a goal-driven decision process that ensures that all relevant goals are considered; the character and current condition of forestland are known; alternatives to manage the land are designed and tested; the future forest under each alternative is simulated; and the alternative selected achieves the owner's goals. NED-2 is designed to link with the NedLite package for field data collection using a handheld PDA, and is constructed to be easy to link to third-party applications. The NED process is being field tested to demonstrate its utility and identify weaknesses. The resource goals addressed by NED include timber production, visual qualities, water quality and quantity, wildlife habitat, forest health, and ecology. (Twery et al. 2005)

ProgettoBosco is a Data-Driven Decision Support Systems, aimed at optimizing the data collection on forest and forest management of Italy. With ProgettoBosco a unique, participated and shared information system effective for all forest typologies existing in Italy was accomplished. ProgettoBosco supports technicians to produce forest management plans. ProgettoBosco provides a large number of control variables (manipulation possibilities) divided into two main groups of data: one related to management and environmental features of forest compartment and the other one to specific bioecological management information referred to the forest stand (forest stand, tree plantations, shrubs and pasture. It provides support for specific thematic areas of a problem type: forest planning, silvicultural, certification, conservation, development choices / land use zoning, policy/intervention alternatives. According to Data-Driven Decision Support Systems definition (Power 2008), in ProgettoBosco data can be easily managed, queried, summarized, ad hoc filtered and retrieved also through the help of specific alerts and triggers and a very user-friendly interface. Specific data displays can be also created within report design, generation and storage. A very good integration with MS Excel software, one of the broader software used by foresters to analyze field data, is also ensured. The outputs are shown as texts, tables, charts and maps. (Ferreti et al. 2011)

GISCAME (former: Pimp your landscape – PYL) is used to assess the impact of land cover and land use change scenarios on planning objectives, which can be expressed by ecosystem services or other, to a higher or lower degree aggregated target figures, such as land use functions or sustainability criteria. As a result, alternative land-use scenarios can be visualized and the platform provides a visual feed-back on their impact on the balance of the selected target figures. Currently, the system is applicable for regions up to 10,000 km², which can be divided into so called "working windows" (standard: 100 km²; other dimensions can be defined individually) to support the visualization of land-use pattern and infrastructural details at mesoscale. Considering the technical background, GISCAME is a combination of a cellular automaton technology with GIS features and a multicriteria assessment framework for which standardized routines are available in the graphical user interface. (Frank et al. 2012)

SADfLOR web-based is a Web-Based Forest and Natural Resources Decision Support System. It is a complete decision support system (DSS) that integrates an information system, a supply driven stand level forest simulator and several optimization tools to support forest management planning. The set of forest stands to be simulated is defined through an implicit query triggered as the study area is selected. b) A platform for the definition of the forest management alternatives/prescriptions for the main tree species in Portugal that represent the base for the simulation of forest management alternatives. c) A prescription driven stand level forest simulator – StandSim – that integrates a set of different forest growth and yield models for the most important Portuguese tree species allowing the growth simulation under different user-defined management scenarios. Simulation results are of two types: - Detailed characterization of stands' growth and yield for the planning horizon; - Essential information required to run the decision models. d) An optimization module that encapsulates exact mathematical techniques (Mixed Integer programming, Linear Programing and Goal programming) and Heuristics. The model generator reads outputs from the stand simulator (e.g. harvest volumes) and financial data from the management information module (i.e. interest rate, prices and costs) and creates the coefficients for all needed equations in the problem formulation. Interface with the user is provided through input forms that allow for the specification of the objective function and constraints that define the management problem. Links with external solvers (i.e. commercial software CPLEX and the freeware GLPK) are programmed in the optimization module in order to solve the mathematical models. Alternatively the system may use a metaheuristic to solve the problem without need to use any external solver. e) A solution report module allows the user to analyze results in different formats (e.g. tables, graphs and maps). f) A graphical user interface to support and guide the access to all modules of the DSS. (Barreiro et al. 2013)

Simulator of forest biodynamics (SIBYLA) is a hybrid model containing empirical, process-based and structural modelling principles (Fabrika 2007). The core of SYBILA is a spatially explicit (distance-dependent) empirical tree model that requires input data for individual trees (position, diameter, height, crown parameters, quality parameters). If the data are not available, a forest structure generator is used. The given or generated forest structure is displayed as a 3D forest structure model.

From tree parameters and spatial structure, the calculation model computes all the important outputs for production, biomass, biodiversity, revenues and costs. Forest development is simulated in 1-year time-steps using mortality, disturbance, thinning, competition and increment models, as well as a model of forest regeneration. It is directly parameterized for 5 basic tree species: common beech, pedunculate or Sessile oak, Norway spruce, silver fir, and Scots pine. In total, 26 different tree species can be simulated, but some of them are derived by modifying the growth processes of the 5 basic tree species. The mortality model focuses on intrinsic and growth-dependent mortality (Fabrika 2007). The disturbance model addresses induced tree mortality caused by external disturbance factors. It is based on modelling risk and incorporates the probabilities of hazard, exposure and vulnerability for different disturbance agents: wind, snow, ice, bark beetles, timber borers, defoliators, wood-destroying fungi, air pollutants, drought, fire and illegal cutting (Fabrika and Vaculčiak 2009). Different types of thinning can be simulated: from below, from above, neutral thinning, target trees method, target dimensions method, target frequency distribution method, geometric method, and interactive thinning (Fabrika and Ďurský 2005). The competition model is based on the crown light competition index (KKL) proposed by Pretzsch (1995). The age-independent increment model simulates tree diameter and height increments based on the reduction of their growth potential. Growth potential is defined according to the ecological site classification proposed by Kahn (1994), based on climate and soil characteristics, and modified to reflect the competition pressure of trees and tree vitality, as determined by tree crown size. If tree age is unknown, it is derived from the growth potential and the current tree height at the beginning of the growth period. The regeneration model is an ingrowth model that generates new tree generation in a forest stand (Merganič and Fabrika 2011). This model is composed of individual-tree generator sub-models along with a diameter and height distribution model for the new generation and a sub-model for locating regeneration in the stand.

SILVA 2.2 is a single-tree-based, position-dependent simulation model designed for operating at the stand or large-area (landscape) level. It includes the most important tree species and site conditions in Central Europe. The model can handle different input data resolutions. The minimum input information required at stand level is the quadratic mean diameter and number of trees per hectare for each species in the stand. Maximum input consists of a list providing diameter at breast height (dbh), height, height to crown base, crown diameter, and position for each tree. The site information needed is restricted to a minimal set of climatic and soil variables that are usually available to practitioners. For large-area simulations, the SILVA interface handles grid-based forest inventory data, which it uses to simulate landscape-level scenarios in one run. SILVA growth functions describe the growth reaction of each tree, according to given size and site conditions, and the competition exerted by its neighbors. All SILVA functions exclude stand or tree age as an explanatory variable, so the model is not restricted to even-aged pure stands. SILVA can simulate a broad range of treatments, from traditional thinning from below to selective thinning to target-diameter felling. Different types and intensities of thinning interventions or final harvests can be applied at stand and landscape levels in one simulation run. Model output is designed for multicriteria scenario assessment, covering classic growth and yield information as well as financial parameters and indicators for forest structure and diversity. Special landscape-level constraints such as habitat or protection areas can be considered by stratifying the inventory data accordingly and defining specific treatments for strata with constraints. SILVA does not command an automatic optimization algorithm. Optima are usually approximated manually by sensibly defining and modifying scenario settings. (Bravo et al.)

2.14.3.3 Assessment of relevant tools

A summary assessment of tools that can be used for the development of forest and landscape management is provided in appendix 5.9 (Table 57).

2.15 M71: Models for estimating air quality and corresponding risk for human health during forest fires

2.15.1 Introduction

Wildfires can produce significant amounts of pollutants that can have negative effects on air quality and health of first fire responders, nearby citizens and distant populations located in the same direction in which the wind is blowing (CAIF et al., 2021). Biomass burning episodes can contribute to the formation of a harmful complex mixture of multiple gaseous, particulate, organic and inorganic compounds, as well as heat energy releases into the atmosphere (Reisen et al., 2015), (Monteiro et al., 2014) The primary emissions that affect air quality are fine particulate matter (PM2.5 - particles with aerodynamic diameters that are 2.5μm or smaller), carbon monoxide (CO), oxides of nitrogen (NOX), sulfur dioxide (SO2) and volatile organic compounds (VOCs) (Urbanski et al., 2014). Subsequently, the VOCs and NOX participate in the photochemical production of PM2.5 and ozone (O3) that must be taken also in consideration (CAIF et al., 2021).

The health risks of exposure to wildfires are directly related to the toxicity of their components, the characteristics of the exposure (e.g., frequency, duration), as well as the degree of vulnerability of the exposed population (people with respiratory problems or asthma, smokers, people with cardiovascular diseases, pregnant women, elderly and children) (Kourkouta et al., 2021). A large number of studies points out that the wildfire smoke exposure is associated with Respiratory Morbidity (Asthma, Chronic Obstructive Pulmonary Disease (COPD), Respiratory Infections), Cardiovascular Morbidity, Birth Outcomes Effects, Mental Health Disorders and Mortality (Reid et al., 2016).

The effect on air quality of smoke from forest burning has been a major research topic. Many methods to estimate wildfire emissions and to simulate and forecast dispersion of smoke have been developed. In addition, plenty of air quality indexes around the world are adopted to inform the public how polluted the air currently is or how polluted it is predicted to become. What follows is a non-exhaustive list of models, indexes and tools that can be found in the relevant literature.

2.15.2 Relevant models

2.15.2.1 Overview of relevant models

The following tables (Table 29-Table 31) provide an overview of models that are useful for estimating air quality and corresponding risk for human health.

More specifically, Table 29 provides an overview of models focused on the estimation of smoke dispersion.

Table 29: Overview of models for estimating smoke dispersion.

Model Code	Model Name	Nature of Model	Applicability	Main Capabilities	Main Restrictions	Implementations
M71.SD1	VALBOX	Mathematical	Phase B	Predicts ground level concentrations of particulate matter and gaseous pollutants under stagnation conditions in valleys.	Emissions are uniformly distributed within the box volume. Finer time resolution would require subdividing the airshed into smaller boxes.	Part of the Tiered Smoke Air Resource System (TSARS)
M71.SD2	VSMOKE	Mathematical	Phase B	A Gaussian plume model for predicting concentrations of fine particulate matter and cross-plume visibility from prescribed fires.	Plume rise is not incorporated. Assumption that all smoke stays within the mixed layer limits its applicability.	http://weather.gfc.state.ga.us/GoogleVsmoke/vsmoke-Good2.html https://webcam.srs.fs.usda.gov/tools/vsmoke/smoke.zip
M71.SD3	SASEM	Mathematical	Phase B	A Gaussian plume model that predicts ground-level particulate matter and visibility impairment from single fires.	Uses simplified assumptions (steady-state, homogenous weather and all smoke confined to mixed layer). Tends to overpredict effects.	https://legacy.azdeq.gov/environ/air/smoke/download/sasem4.exe

M71.SD4	CALPUFF	Mathematical	Phase B	Assesses transport of pollutants and their effects, on a case-by-case basis, or for certain near-field applications involving complex conditions.	Difficulties in finding and translating information on complex fire activity into suitable source inputs.	CALPUFF Modeling System (CALMET, CALPUFF, and CALPOST) BlueSky
M71.SD5	HYSPLIT	Mathematical	Phase B	A system for computing simple air parcel trajectories and complex dispersion and deposition simulations	Inability to account for secondary chemical reactions. Reliance on the input meteorological data's resolution, which can have coarse temporal and spatial resolution.	HYSPLIT HYSPLIT – WEB BlueSky
M71.SD6	FLEXPART	Mathematical	Phase B	A Lagrangian transport and dispersion model suitable for the simulation of a large range of atmospheric transport processes.		FLEXPART
M71.SD7	Daysmoke	Mathematical / Empirical	Phase B	A plume rise and dispersion model for simulating smoke. Includes algorithms to simulate the role of multiple updraft cores	Local scale. Developed specially for prescribed burning smoke.	
M71.SD8	CMAQ	Mathematical	Phase B	A sophisticated 3D Eulerian grid chemical transport model for studying air pollution from local to hemispheric scales.		https://github.com/USEPA/CMAQ
M71.SD9	WRF-SFIRE	Mathematical	Phase B	A coupled fire-atmosphere model for fire and smoke modeling. Evolves the fire front on an Eulerian grid in time.	Level set fireline.	https://github.com/openwfm/WRF-SFIRE
M71.SD10	WFDS	Mathematical	Phase B	A physics-based fire model for landscape-scale high-resolution modeling. Uses a finite-volume, large eddy simulation approach to model turbulence.	Computationally expensive. Local scale. Relatively near-field smoke plume rise and downwind transport.	https://github.com/firemodels/fds FDS-SMV
M71.SD11	FIRETEC	Mathematical	Phase B	A physics-based fire model for landscape-scale high-resolution modeling. Uses a finite-volume, large eddy simulation approach to model turbulence.	Computationally expensive. Local scale. Relatively near-field smoke plume rise and downwind transport.	

Table 30 provides an overview of models for estimating emissions.

Table 30: Overview of models for emissions estimation.

Model Code	**Model Name**	**Nature of Model**	**Applicability**	**Main Capabilities**	**Main Restrictions**	**Implementations**
M71.EE1	BURNUP	Mathematical / Empirical	Phase B	It is a physical model of heat transfer and burning rate of woody fuel particles as they interact over the duration of a burn.	It is limited in its application and may not fully encompass the broad range of environmental conditions and fuel complexes that are burned in the region.	FOFEM

M71.EE2	CONSUME	Mathematical / Empirical	Phase B	Predicts fuel consumption by fire phase (flaming, smoldering, residual smoldering), heat release, and pollutant emissions.	It is limited in its application and may not fully encompass the broad range of environmental conditions and fuel complexes that are burned in the region.	Bluesky Fuel and Fire Tools
M71.EE3	FEPS / EPM	Mathematical	Phase B	Manages data concerning consumption, emissions and heat release characteristics of prescribed burns and wildland fires.	Because of the relative complexity of the data necessary to define an entire burn, users are not allowed to create one from blank input screens.	EPM FEPS Fuel and Fire Tools
M71.EE4	Seiler and Crutzen	Mathematical	Phase B	Estimates the production of charcoal and the atmospheric emissions of trace gases volatilized by burning.	Variables that contribute to the emissions estimation are affected by uncertainties.	Majority of Emissions Estimation Models

Table 31 provides an overview of air quality indexes.

Table 31: Overview of air quality indexes.

Model Code	Model Name	Nature of Model	Applicability	Main Capabilities	Main Restrictions	Implementations
M71.AQI	EAQI	Mathematical	Phase B	Displaying up-to-date information for Europe, users can gain insights into the air quality in individual countries, regions and cities.	The index is calculated hourly for more than 3.500 monitoring stations across Europe, using data reported by EEA member countries and forecast as provided by CAMS.	https://airindex.eea.europa.eu/Map/AQI/Viewer/
M71.AQI	US AQI	Mathematical	Phase B	The U.S. AQI is index of U.S. Environmental Protection Agency for reporting air quality.	Towns and cities with 350,000 or fewer inhabitants are not required to report the AQI. Some state or local agencies may not submit data	https://www.airnow.gov

2.15.2.2 Description of relevant models

Smoke Dispersion

Various types (box, Gaussian, puff, particle, Eulerian, full physics) of models have been developed that attempt to investigate the wildfire smoke dispersion (Doodrick et al., 2012). These include:

M71.SD1 VALBOX

VALBOX (Ventilated Valley Box Model) is a screening model intended to estimate ground level concentrations of particulate matter and gaseous pollutants in mountain valleys under stagnation conditions (Sestak et al., 1989). As an example of box models used for fire management, it assumes that an airshed can be represented by a simple box in which emissions are immediately well-mixed throughout, ignoring the plume rise and dispersion processes. Compared with a box model, a plume model offers a more realistic description of a smoke plume. Plume models define the source as a point or specific area encompassing the fire, while smoke, whose dispersion is represented by a Gaussian distribution, is transported in the direction defined by a usually constant speed wind. They do not require detailed weather inputs and they prove to be very useful when meteorological information is limited.

M71.SD2 VSMOKE – M71.SD3 SASEM

VSMOKE (Lavdas et al., 1996) and **SASEM** (Simple Approach Smoke Estimation Model) (Riebau et al., 1998) are typical examples of wildfire Gaussian plume models that have been developed. **VSMOKE** gives stakeholders a quick description of smoke behavior given their planned fire activity and prevailing weather conditions. However, it ignores plume rise and assumes that all smoke stays within the mixed layer, which is applicable only for small prescribed fires. SASEM predicts ground-level particulate matter concentrations from single fires in flat to gently rolling terrains with specified fuel types. Like VSMOKE, **SASEM** borrows simplified steady-state assumptions, which reduce the reliability of the results, but it makes use of internally calculated plume rise. Many of the limiting assumptions of the Gaussian plume models are no longer apply in case of puff models. In a model of this class, a smoke plume corresponds to a collection of independent 'puffs' released throughout the duration of a fire event, with each 'puff' representing a volume that has specific concentration of pollutant. As time of the event passes, these puffs are transported by winds that vary in both space and time. In addition, the puffs expand with time due to the processes of entrainment and diffusion. The pollutant amount decreases within the puff, as the puff volume increases.

M71.SD4 CALPUFF – M71.SD5 HYSPLIT

CALPUFF (Scire et al., 2000) and **HYSPLIT** (Stein et al., 2015) belong to the class of puff models. **CALPUFF** is an advanced Lagrangian–Gaussian non-steady-state model that estimates the effects of pollutants' transport in special cases of meteorological conditions. **HYSPLIT** is a computer model that applies both Lagrangian and Eulerian approaches and is adopted to estimate air parcel trajectories and to present the direction and distance of emission transport. Despite improvements in the model, it cannot handle secondary chemical reactions and is directly dependent on the input meteorological data's resolution. In particle (or random walk) models each particle corresponds to an infinitesimal air parcel containing a fixed mass of pollutant and the smoke diffusion is considered as a direct result of the movement of particles rather than a parameterised process. This more direct simulation of dispersion has as a consequence significant computational costs as the number of particles required to represent the plume is multiple of the number of puffs. The number of particles within a given volume determines pollutant concentrations.

M71.SD6 FLEXPART

FLEXPART (Pisso et al., 2019) is a Lagrangian particle dispersion model suitable for the simulation of the long-range and mesoscale atmospheric transport processes. Apart from diffusion, it is designed to simulate dry and wet deposition, and radioactive decay and linear chemistry. It can be applied not only in forward but also in backward mode.

M71.SD7 Daysmoke

Daysmoke (Achtemeier et al., 2011) is an empirical-stochastic plume rise and dispersion model designed to simulate multiple-core updraft fire smoke plumes, movement, fallout, fluctuation, and burn emissions from prescribed fire events. HYSPLIT can also be applied as a particle model. In contrast to the material description and the moving coordinate frame adopted by Langrangian models (like puff and particle models), Eulerian models (like grid models) make use of field description and a reference frame that is fixed in both space and time. A grid model could be thought of as a collection of interconnected box models that together form a regular lattice. Although the fixed coordinates of Eulerian models make it difficult to track the motion of an individual particle or plume, grid models are capable of investigating the cumulative effects of several plumes. Grid models also facilitate modeling chemical transformations among pollutants and the environment, making them especially useful for examining local photochemical phenomena.

M71.SD8 CMAQ - M71.SD9 WRF-SFIRE - M71.SD10 WFDS - M71.SD11 FIRETEC

CMAQ (Community Multiscale Air Quality Model) (Byunet al., 2006) is a multiscale three-dimensional Eulerian grid chemical transport model developed to investigate air pollution from local to hemispheric scales. The CMAQ simulates various chemical and physical processes that are crucial for understanding wildfire emissions transformations and distributions.

Finally, there is a class of models that reduce the horizontal extent of the grid volumes from several kilometers down to a few tens of meters or less, which make them capable of explicitly resolving complex processes that influence plume development, such as entrainment. These models are referred to as full physics models and **WRF-SFIRE** (Mandel et al., 2011), **WFDS** (Mell et al., 2007) and **FIRETEC** (Linn et al., 2005) belong to this class.

Emissions Estimation

Wildfires are large sources of pollutants and heat releases in the atmosphere. These biomass burning events widely differentiate in three aspects: which emissions are produced, what their concentrations are and how much energy is released. These products have a significant negative impact on air/environmental pollution, climate change and health.

M71.EE1 Burnup - M71.EE4 Seiler and Crutzen

For almost four decades the state of the art in calculating the emissions of wildfires has been based on the approach presented by **Seiler and Crutzen** (Seileret al., 1980). This method adopts information about the burnt area extent, the type and amount of biomass (fuel types, fuel loads), and the conditions, the type of combustion under which wildfires take place (combustion efficiencies/completeness); finally, emission factors are attributed to each component (chemical compounds and particles) to estimate the amount of emissions. The **Burnup** model (Albini et al., 1995), as updated in FOFEM (Lutes et al., 2020) version 6.7, provides separate calculations of different combustion types in each time step for each fuel component. It is based on the assumption that flaming combustion cannot be supported below an intensity of about 15 kW/m2. All shrub, herb, foliage, branch and litter components are assumed to burn in the flaming phase. All duff is assumed to be consumed in the smouldering phase. Emission factors adopted for woody fuels are determined by the estimated intensity. In case of an intensity less than 15 kW/m2 smouldering emission factors are applied while otherwise flaming ones. At each Burnup time step the percent of total fuels in the respective phases of combustion is estimated and the appropriate emission factors are adopted to calculate total emissions at each time step.

M71.EE2 Consume

Consume (Prichard et al., 2006) makes predictions about fuel consumption, pollutant emissions, and heat release for fuelbeds and burn units based on multiple factors including environmental conditions and fuel characteristics. Consume applies two alternative approaches for estimating emissions. The first approach is adopted for non-piled fuels and estimates emissions based on a set of emission factors which are determined by the type of fuel (like ponderosa pine, mixed conifer, hardwood, Douglas-fir) and the conditions - combustion phase (flaming, smouldering, and residual smouldering) of the burn. In the second approach, that of piled fuels, the soil content of the accumulation determines the emission factors.

M71.EE3 FEPS/EPM

The first edition of **Emissions Production Model** (EPM) (Sandberg et al., 1984) was designed to support managers in estimating and mitigating the rates of heat releases, carbon gas and particles emissions from controlled burns. Throughout the update process of EPM, significant improvements were made in terms of accuracy, usability and applicability of the model. The estimation method was totally reformulated and allowed both novice and advanced users to produce reasonable and refined results respectively. The model has been renamed **FEPS** (Anderson et al., 2004). The distribution of total burn consumption values throughout the duration of the burn is utilized to produce data on hourly emissions and releases. The managed data encompasses a multitude of variables, such as the quantity and moisture of different fuel strata, hourly meteorological conditions, and various other factors. It is noteworthy that the latest version of the Fire Emissions Production Simulator (FEPS) is situated within the Fuel and Fire Tools (FFT) (University of Washington et al., 2023).

Air Quality Indexes

An air quality index is a measure that has been created by government agencies to inform the public about the current or the anticipated level of air pollution. As the level of air pollution increases, so does the air quality index, which in turn increases the risk to public health. Typically, the first groups to experience the negative effects of poor air quality are children, the elderly, and those who suffer from respiratory or cardiovascular problems. Different countries have their own indexes, which correspond to different national air quality standards. Two indicative examples are presented:

M71.AQI1 - EAQI

By presenting up-to-date information, the - M71.EE4 Seiler and Crutzen (**EAQI**) (EEA et al., 2023) enables its users to gain valuable knowledge regarding the air quality of various countries, regions, and cities in Europe. The Index relies on concentration measurements for a maximum of five major pollutants, i.e., particulate matter (PM10), fine particulate matter (PM2.5), ozone (O3), nitrogen dioxide (NO2) and sulphur dioxide (SO2). It illustrates the possible influence of air quality on health, as determined by the pollutant with the most detrimental health effects due to its concentration levels and adopts six discrete levels (i.e., Good, Fair, Moderate, Poor, Very Poor and Extremely Poor) that has a specific colour. The hourly calculation of the index includes over 3,500 monitoring stations throughout Europe, making use of a combination of data provided by EEA member countries and estimated air quality levels supplied by the Copernicus Atmospheric Monitoring Service (CAMS). By default, the index illustrates the state of air quality three hours ago. In addition, users have the option to choose any hour within the previous 48 hours and observe estimated values for the ensuing 24 hours.

M71.AQI2 - AQI

The **U.S. Air Quality Index** (**AQI**) (AirNow et al., 2023) is EPA's (Environmental Protection Agency) index for monitoring air quality. Think of the AQI as a measure that ranges from 0 to 500, serving as a benchmark for air quality. As the AQI value rises, so does the level of air pollution and the associated health risks. The AQI is classified into six distinct categories. Furthermore, each category has been assigned a specific colour to aid in quick identification of air quality levels in local communities, enabling individuals to determine if they are reaching unhealthy levels. The major pollutants considered in this case are: ground-level ozone, particle pollution (including PM2.5 and PM10), carbon monoxide sulphur dioxide and nitrogen dioxide.

2.15.2.3 Assessment of relevant models

In appendix 5.10, Table 58 provides a summary assessment of models that are used for estimating smoke dispersion. Table 59 provides a summary assessment of models that are used for estimating emissions. Table 60 provides a summary assessment of popular air quality indexes.

Based on the assessments provided, models that are extensively implemented, well-understood, and easy to apply can be selected. Specifically, the SILVANUS team has implemented a Gaussian model similar to VSMOKE model (M71.SD2) as our base model and have improved it to generate the necessary geojson files that can be seamlessly integrated into the SILVANUS cloud system. For emissions estimation, SILVANUS opted to adopt the equations of the Seiler and Crutzen model (M71.EE4). Finally, since both air quality models, M71.AQI1 and M71.AQI2, yield identical scores, either can be utilized.

2.15.3 Relevant tools

2.15.3.1 Overview of relevant tools

Table 32 provides an overview of tools that can be used for the estimation of air quality and corresponding risk for human health.

Table 32: Overview of tools related to estimating air quality and corresponding risk for human health.

Tool Code	Tool Name	Installability	Applicability	Main Capabilities	Main Restrictions	Integrated Models
T71.1	FOFEM (Smoke Emissions - BURNUP)	Windows application Needs Windows 7 or higher	Phase B	Provides quantitative fire effects information for smoke emissions	National in scope. Uses four geographical regions: Pacific West, Interior West, North East, and South East of USA.	M71.EE1
T71.2	BlueSky	Linux application Standard Linux - UNIX	Phase B	Links together a variety of state-of-the-art models of meteorology, fuels, consumption, emissions, and air quality, and offers multiple model choices at each modeling step.	Available in the USA.	M71.SD4 M71.SD5 M71.SD8 M71.EE2 T71.1 (Emissions)
T71.3	Fuel and Fire Tools	Windows application Needs Windows 7 or higher Requires .NET libraries (version 4 or higher) Java (version 1.6/6 or higher)	Phase B	FFT is a software application that integrates several fire management tools into a single user interface.	National scope (USA). The FFT tools make point-based calculations of fuel characteristics and potential fire behavior. Fuelbeds must be characterized accurately.	M71.EE2 M71.EE3
T71.4	EFFIS (forest fire emissions module)	Available Online (Web-based) Latest versions of web browsers	Phase B	Estimates trace gases emissions from vegetation fires based on fuel types, meteorological.	The 3hr resolution of the fine dead fuel moisture content. The fine spatial resolution (250m) of the fuelmap.	M71.EE4
T71.5	CAMS (GFAS)	Data available from the Atmosphere Data Store (ADS) Latest versions of web browsers	Phase B	Assimilates fire radiative power observations from satellite-based sensors to produce daily estimates of emissions from wildfires and biomass burning.	Data are available globally on a regular latitude-longitude grid with horizontal resolution of 0.1 degrees from 2003 to present. Data through the ECMWF public Web API service ended on 9/7/22.	Fire Radiative Power (FRP)

2.15.3.2 Description of relevant tools

The following paragraphs provide a description of the tools summarized above.

T71.1 FOFEM

The **FOFEM** - First Order Fire Effects Model (Lutes et al., 2020) tool has been specifically designed to quantitatively determine the direct or indirect consequences of either a prescribed fire or wildfire, utilizing four distinct metrics. These metrics include tree mortality, fuel consumption, the production of emissions or smoke, and soil heating. This tool has been designed to be used for evaluating fire impacts and severity, as well as for planning prescribed fires that effectively meet resource requirements and other related applications. The tool has a national scope and partitions the United States into four distinct regions. The required inputs vary depending on the specific output that the user desires to produce among the four alternative options (USDA et al., 2023). In order to facilitate the process, default values are already assigned to the majority of the essential parameters. However, users are able to personalize these values by utilizing their own data. The inputs include the classification system and cover type of a geographical region, the general burning conditions, the fuel type present in the region, the fuel loading by size class and the fuel moisture, the percentage of crown burned and lastly, for soil heating only, the soil texture and the percentage of soil moisture. Some of the outputs are the loading before burning, the loading during combustion, and the loading after burning, the reduction in percentage and the depth of the consumed duff, and the percentage of exposed mineral soil, the emissions of particular pollutants, total consumption and duration takes place in flaming and smoldering combustion. Tree mortality results are produced in the form of the proportion of tree mortality based on species and size category, as well as the canopy cover before and after a fire event.

T71.2 BlueSky

BlueSky (Larkin et al., 2009) is a modeling framework that integrates a large set of autonomous models pertaining to fire information, fuel loading, fire consumption, fire emissions, and smoke dispersion. At every stage of processing, BlueSky modularly offers a plethora of distinct models to select from, which enables the creation of many diverse pathways. Within the tool one can study the fuels information of the available maps, estimate the total and hourly fire consumption, calculate the emissions concentrations, determine the vertical plume characteristics, study possible smoke trajectories parcels and predict downstream smoke concentrations produced by a fire. Furthermore, it is a straightforward task to incorporate your module by designing a basic wrapper that executes your code in its native format. BlueSky is identified as a valuable tool for the purpose of integrating data pertaining to fire incidents, fuels, and meteorology from various fire events in order to compute emissions, trajectories, and concentrations.

T71.3 FFT

Fuel and Fire Tools (FFT) (FERAT et al., 2023) is an application that employs fuels data categorized as fuelbeds in order to enable users to perform diverse calculations pertaining to fire behavior and emissions. These calculations include the estimation of fuel consumption, both surface and crown fire behavior, pollutant emissions (including carbon emissions), and heat release. The tools of FFT facilitate the computation of fuel characteristics and the assessment of potential fire behavior on a point-by-point basis, without simulating the spread of fire across landscapes (ASDA et al., 2023). Inputs may differ based on the particular application. Nevertheless, all applications necessitate the selection of fuelbeds that closely approximate the evaluation area. Users have the capability to choose from an existing inventory of fuelbeds or customize the descriptions. Environmental inputs are additionally necessary and vary depending on the specific application. Outputs comprise estimations of hourly fuel consumption, pollutant emissions, and attributes of heat release.

T71.4 EFFIS

The **European Forest Fire Information System** (EFFIS) (San-Migul-Ayanz et al., 2012) is comprised of a modular web-based geographic information system that offers both near real-time and historical information pertaining to forest fires in the European, North African and Middle Eastern regions. It encompasses the comprehensive evaluation of the complete fire cycle, including valuable information on pre-fire circumstances, as well as the evaluation of the subsequent fire damages. Through EFFIS, a variety of specialized applications are accessible, including Current Situation Viewer, Current Statistics Portal, Long-term fire weather forecast, Wildfire Risk Viewer, Firenews and Data Request Form.

T71.5 CAMS

The **Copernicus Atmosphere Monitoring Service** (CAMS) (ECMWF , 2023) aims to provide continuous data and information pertaining to the chemical composition of the Earth’s atmosphere. It gives an overview of the current state, projects the situation out a few days ahead, and does a thorough analysis of data records for past periods. CAMS comprehensively monitors the worldwide phenomena encompassing air pollution, greenhouse gasses, solar energy, and climate forcing. The CAMS Global Fire Assimilation System (GFAS) (ECMWF et al., 2023) employs the assimilation of fire radiative power (FRP) observations derived from sensors mounted on satellites in order to estimate daily the emissions resulting from biomass burning. It also furnishes information regarding the estimated heights of injections obtained through fire observations as well as meteorological information from the operational weather forecasts provided by ECMWF.

2.15.3.3 Assessment of relevant tools

A summary assessment of tools that can be used for the estimation of air quality and corresponding risk for human health is provided in appendix 5.10 (Table 61).

2.16 M72: Models to simulate and support evacuation needs due to forest fire event

2.16.1 Introduction

During the summer months, the Croatian coast is exposed to large fires in open space that can have consequences for people and property and pose a threat to the resident population as well as a large number of tourists who are in the Republic of Croatia. When the spread of large open space fires threatens urban areas and tourist facilities where a large number of tourists are located, it is necessary to carry out the evacuation of vulnerable persons as well as their property (vehicles). Evacuation as a civil protection measure is a very demanding activity to implement and must be planned and implemented as soon as possible to protect people's health and lives. Following you can find consideration and proposals based on Croatian experience.

Main consideration to have in mind regarding evacuation:

- Evacuation is undertaken to achieve maximum protection of citizens from the threat or consequences of an extraordinary event caused by open space fires.
- Evacuation aims at temporary relocation, i.e., moving citizens, property and domestic animals from a threatened or immediately threatened area from open space fires to non-threatened areas.
- It is necessary to develop early warning and alarm systems with the aim of informing the resident population and tourists in a timely manner about taking the necessary protection and self-protection measures in the event of an open space fire.
- Through education, it is necessary to raise public awareness about the implementation of the evacuation ordered by the population and operational forces.
- Special care during evacuation should be given to people with special needs and patients from medical institutions.
- It is necessary to carry out regular training of the operational forces of the civil protection system in cooperation with legal entities from the tourism sector before the start of the fire season.
- Conducting regular inspections before the fire season against legal entities in the tourism sector.
- Implementation of modern technologies to support decision-making and implementation of evacuations, such as interactive databases, dynamic risk assessments, surveillance cameras and drones.

Proactive management model should include three main areas:

1. Planning
2. Early warning systems
3. Training and exercises

A proactive management model for evacuation in case of open fires should involve a systematic and strategic approach to minimize the risks of fires and prepare for potential evacuations.

Planning

Planning for evacuation in case of open space fires is critical to ensure the safety of people. Several aspects should be taken to plan for evacuation:

- *Identify evacuation routes* from the open space area in advance. This can include identifying primary and secondary routes, as well as any obstacles that may impede evacuation.
- *Identify safe locations* where people can go in case of an evacuation. These locations can include nearby shelters, community centers, or other designated areas.
- *Develop evacuation (emergency) plan* that includes procedures for evacuation, communication, and response. This should be communicated to all stakeholders, including staff, volunteers, and visitors.
- *Conduct regular evacuation trainings and exercises* to ensure that everyone knows what to do in case of an emergency. This can help identify any issues with the evacuation plan and improve overall preparedness.
- *Install signage* throughout the open space area to direct people to evacuation routes and safe locations. This can include directional signs, maps, and emergency contact information.
- *Establish communication channels* for emergency notifications and updates. This can include email, text message, social media, or other means of communication, like tailored made mobile applications.
- *Consider the needs* of people with disabilities, elderly, or those with limited mobility. Ensure that there are appropriate accommodations and assistance available for these individuals.
- *Coordination among operational forces*, including fire and police departments, to ensure that they are aware of the evacuation plan and can provide assistance as needed.

In most cases, the executive body of the local self-government unit ensures the conditions for evacuation. The preventive implementation of forced evacuation can be ordered by the head of civil protection at local level supported by fire commander and police. This decision is mandatory for all those people affected.

A high-quality evacuation (emergency) plan requires the creation of a textual and graphic part with elements essential for handling in the event of an emergency. The plan must enable the organized evacuation of the area and the provision of assistance to persons who cannot evacuate on their own, and the aim is to eliminate or reduce the risks caused by an extraordinary event. Everyone (local population and operational forces) should be familiar with the evacuation (emergency) plan that applies to them.

Early warning systems

An early warning system for evacuation is critical to ensure the safety of people in case of an emergency. The most important reason for an early warning system is to ensure the safety of people. In the event of an emergency, a timely warning can allow people to evacuate quickly and avoid harm.

With an early warning system in place, emergency responders can be quickly alerted and mobilized to respond to the situation. This can help minimize the damage caused by the emergency. An early warning system helps people and communities to be better prepared for emergencies. This includes developing emergency plans, conducting training and exercises, and identifying evacuation routes. It helps to minimize panic and confusion during an emergency. When people are informed and prepared, they are less likely to panic and more likely to follow emergency procedures. This is especially important for those who are more vulnerable such as the elderly, disabled, or young children.

Early warning systems can help to reduce property damage by allowing people to take necessary precautions such as shutting off utilities, securing valuable possessions, and moving items to higher ground. It provides vital information that enables people to make informed decisions and take necessary actions to protect themselves, their families, and their property.

An early warning system for open space fires could include several components. Here are some areas that are necessary to be involved:

- *Smoke detection sensors* could be installed in key locations throughout the open space area. These sensors would be able to detect the presence of smoke and trigger an alarm.
- *Heat detection sensors* could also be installed in key locations. These sensors would be able to detect a sudden increase in temperature, which could indicate the start of a fire.
- *Monitoring the weather conditions* can provide important information about the potential for fire. For example, dry and windy conditions increase the risk of fire. Installing weather stations in the open space area can provide real-time data on temperature, humidity, wind speed, and precipitation.
- *Surveillance cameras* could be installed in key locations to monitor for any signs of smoke or fire. These cameras could be linked to an alert system that triggers an alarm if smoke or fire is detected.
- *Mobile applications* could be developed to allow citizens to report any signs of smoke or fire they observe. These apps could use GPS data to pinpoint the location of the report and alert authorities/population.
- *Raising awareness* of fire safety among the local community can also help prevent fires. This could include educational campaigns, outreach to local schools, and public service announcements.

Overall, an effective early warning system for open space fires would combine several of above components to provide a comprehensive approach to fire prevention and response.

Training and exercises

Training and exercises are critical to ensure that operational forces and population are prepared for an evacuation in case of open fires. Exercise is one way of training for evacuation. The goal is to ensure proper movement and execution of procedures to successfully leave the threatened areas, but also to remove the fear of moving through smoky or poorly visible areas. Following are steps that can be taken in systematic approach for capacity building:

- *Develop training material*s that cover fire safety, evacuation procedures, and safe zones. These materials can include written guidelines, videos, and presentations.
- *Provide hands-on training* on how to use fire extinguishers, first aid kits, and other emergency equipment. This helps to build confidence and familiarity with the equipment.
- *Conduct regular evacuation exercises* to test the effectiveness of the evacuation (emergency) plan and identify areas for improvement. These exercises can involve operational forces and population.
- *Coordinate with operational forces*, such as fire departments, police and civil protection, to participate in the exercises and provide feedback on the effectiveness of the evacuation plan.
- *Evaluate the effectiveness of the training and exercises* to identify areas for improvement. This evaluation can include feedback from operational forces and population.
- *Update the evacuation (emergency)* plan based on the evaluation of the training and exercises, update the evacuation plan to ensure that it reflects best practices and lessons learned.
- *Provide ongoing training* to ensure that operational forces and population are prepared for emergencies. This can include refresher courses and new training materials as needed.

Training and exercises are critical to ensure that staff, volunteers, and population are prepared for an evacuation in case of open fires. By providing hands-on training, conducting evacuation exercises, coordinating with emergency responders, evaluating the training and exercises, updating the evacuation plan, and providing ongoing training, open space managers can help to ensure the safety of everyone in the open space area during emergencies.

Final remarks

Evacuation management in the event of an open space fire is critical to ensure the safety of people, property, and the environment. Overall, managing evacuation in the event of an open space fire requires careful planning, coordination, and communication. It is essential to act quickly and efficiently to ensure the safety of all individuals (operational forces and population) involved.

The system for early warning SRUUK is an information system implemented at the level of the Republic of Croatia with the aim of timely informing citizens about the crisis situation with the possibility of sharing instructions for action in a threatened area via mobile phones. The system is a complement to the classical alarming through sirens and electronic media, in case of great danger, all alarming channels will be used. Through the system, it is possible to send a warning for any situation that threatens the lives and safety of people, the environment and property. All members of the European Union must have such systems based on EU Directive 2018/1972, the so-called EECC Directives. Sirens, loudspeakers, and electronic media are used to alert and inform the population about dangerous situation and to tigger evacuation process when necessary.

Ministry of Interior sends a request to mobile operators to send a specific message to the desired area, mobile operators have information about the devices in that area. Messages are sent to all users of mobile devices, citizens of the Republic of Croatia and foreign citizens who are currently in the crisis area, for the purpose of protection and rescue (RoC, 2023a). Alerting the population is carried out by broadcasting unique warning signs, which are prescribed by the Regulation on unique warning signs. Fire brigades independently give the signal "fire alarm" through their own means of alarming and are obliged to immediately inform the Centre 112 (RoC, 2023b).

SRUUK is a system that will contribute to raising the overall ability to react and increase the capacity of the crisis management system in the Republic of Croatia by raising the level of readiness of the Ministry of the Interior, as the central body in the national civil protection system, for prevention and timely and appropriate reactions in cases of occurrence disasters or major accidents caused by natural, technical-technological or human factors. SRUUK have wider and direct impact to population (share messages to mobile phones located in the danger area with alert and info on action) in comparison with sirens which is older system without detailed info on the necessary action.

2.16.2 Relevant models

2.16.2.1 Overview of relevant models

Table 33 provides an overview of models for evacuation route planning.

Table 33: Overview of models for evacuation route planning.

Model Code	**Model Name**	**Nature of Model**	**Applicability**	**Main Capabilities**	**Main Restrictions**	**Implementations**
M72-EP.1	Wang et. al.(2014)	Mathematical	Phase B	Estimate fire shape and direction (*), predicts availability in roads in a certain area and time, calculates the safest and fastest available responders route.	Lack of evacuation path estimation, sensitive in the accuracy of measurements of the output of the fire simulation model.	T72-EP.4, T72-EP.10
M72-EP.2	Wang and Zlatanova (2020)	Mathematical	Phase B	Dynamically estimates the safest route based on the safety and length of the road, computes the obstacles, estimates vehicle's speed factor.	No consideration of time, one vehicle navigation.	T72-EP.10, T72-EP.11
M72-EP.3	Kuligowski (2021)	Review	Phase B	Reviews current evacuation decision-making and behaviour in wildfires, Identifies research gaps and develops a future research plan for further data	Lack of model proportion, focus on urban area evacuation	

				collection of fire evacuation concepts, References to wildland-urban interface (WUI) fires.		
M72-EP.4	Beloglazov et. al. (2016)	Mathematical	Phase B	Can predict fire spread, traffic and behaviour and estimate shortest path for evacuation and clearance times	Vehicle numbers do not depend on the time of day, people obey to speed limits and drive to nearest exit, static route selection, all residents receive warnings when sent, constant weather conditions, departure time sensitive to people distribution and area size.	T72-EP.4, T72-EP.7, T72-
M72-EP.5	WUI-NITY	Mathematical	Phase B	Simulates and visualizes human behaviour and wildfire spread during evacuation of WUI communities	Doesn't provide safest evacuation routes.	T72-EP.4
M72-EP.6	Maranghides and Link, (2023). ESCAPE	Guidelines, considerations, processes.	Phase A, B	community hazard reduction; disaster resilience; emergency notification; evacuation; intermix; interface; notification; pre-fire planning; public safety; wildland-urban interface; WUI	The proposed system outlines a path for community leaders to effectively work with first responders before a fire to assess and prepare the community for WUI fire events that can strike with little or no notice.	
M72-EP.7	WISE framework (Pishahnag et al., 2022)		Phase A, B	Wildfire, Egress, Evacuation Planning A Bayesian Belief Network (BBN) in which the components and their dependencies are modeled in a probabilistic manner that considers fire dynamics, human decision-making and traffic model.		WISE platform
M72-EP.8	Carton, 2020	Mathematical.	Phase A, B	wildfires, traffic modelling, fire behaviour	Evacuation modelling coupling traffic and fire behaviour. Fire propagation and spread is modelled simplistically, fire data from satellites may affect the quality of the simulations, not tested for multiple fires.	
M72-EP.9	Ronchi E., 2021	Review of Mathematical models and simulators	Phase A, B	Evacuation; Egress; Human behaviour; Modelling; Simulation; Fire safety		
M72-EP.10	Ahmad et al., 2023	Not exactly model, evaluation of Connected Vehicle model	Phase A, B	connected vehicle; traffic operations; wildfire; evacuation; wildland–urban interface; disaster	Shows traffic delays. No more. Nor widlfire modelling	
M72-EP.11	Siam et al., 2022	Mathematical (agent-based)	Phase A, B	Wildfire evacuation; Evacuation decision-making; agent-based modeling		
M72-EP.12	Ronchi E., and Gwynne S. 2019	Mathematical	Phase A, B	Egress; evacuation		
M72-EP.13	Li et al., 2018	Mathematical, probabilistic	Phase A, B	Wildfire evacuation; trigger modeling; wildfire simulation; traffic simulation; model coupling; GIS		

M72-EP.14	Zhou and Erdogan (2019)	Mathematical (stochastic)	Phase A, B	Wildfire management; Goal programming; Stochastic programming		
M72-EP.15	Veeraswamy et al.	Mathematical (agent-based)	Phase A, B	urban evacuation, evacuation simulation, wildfire, forest fire, disaster management, GIS	pedestrian city scale	MATSIM (EXODUS building evacuation model adapted)
M72-EP.16	Gradjura et al., 2020	Mathematical (NetLogo agent-based)	Phase A, B			
M72-EP.17	Effinger, 2021	Review of evacuation practices (not model)	Phase A, B	Traffic Modeling of Potential Emergency Wildfire Evacuation Routes		

Table 34 provides an overview of models for safe zone estimation.

Table 34: Overview of models for safe zone estimation.

Model Code	Model Name	Nature of Model	Applicability	Main Capabilities	Main Restrictions	Implementations
M72-SZ.1	Butler and Forthofer (2002)	Mathematical / Empiric	Phase B	Can estimate safe zone distance from fires	Sensitive to high height flames, doesn't include cases where firefighters are in the water.	
M72-SZ.2	Butler and Cohen (1998)	Mathematical / Empiric	Phase B	Can estimate safe zone distance from fires	Simple linear model, doesn't include the convection of fire.	

2.16.2.2 Description of relevant models

The following paragraphs provide further information for a selection of five evacuation route planning models presented in Table 33.

M72-EP.1 A data model for route planning in the case of forest fires

Authors in (Wang, et. al. 2014) studied the problem of evacuation paths generation in a real road network during forest fires. To achieve this, they employ a fire simulation model to obtain realistic results about the fire's spread. Additionally, a spatio-temporal data model is utilized to organize dynamic transportation information effectively. Using a modified shortest path algorithm, evacuation paths are computed, enabling first responders to avoid fire-affected areas during the evacuation process.

M72-EP.2 Safe route determination for first responders in the presence of moving obstacles

The presence of moving obstacles in case of wildfires is studied in (Wang and Zlatanova, 2019). Using hazard simulations to predict the movement of hazards and obstacle geometries (type, position and size) authors extend Dijkstra’s algorithm to consider the impact of various types of moving obstacles on road networks and rescue vehicles.

M72-EP.3 Evacuation decision-making and behavior in wildfires

The survey paper by Kuligowski (2021) serves two main purposes: Firstly, it reviews evacuation decision-making and behavior of community residents during wildfires, with a specific focus on the data required for evacuation simulation models. Secondly, it presents the current research and data collected on evacuation decision-making while it identifies research gaps and proposes a future research plan for further data collection.

M72-EP.4 Simulation of wildfire evacuation with dynamic factors and model composition

A novel modeling approach for calculating evacuation paths is presented in (Beloglazov et. al., 2016). This model considers dynamic factors, such as people's behavior and the timing of events, to accurately predict evacuation routes. Furthermore, a new metric called the exposure count is proposed to evaluate the effectiveness of an evacuation, directly quantifying the threat to the population. The paper also introduces an architecture that implements the modeling and simulation workflow, providing a practical framework for applying the proposed approach.

M72-EP.5 The simulation of wildland-urban interface fire evacuation: The WUI-NITY platform

Aiming to enhance situational awareness for responders and residents, authors in (Wahlqvist et. al., 2021) propose a novel modeling platform built on the Unity3D game engine (WUI-NITY). The platform is capable of both visualization and simulation of human behavior and fire spread during wildfire incidents in Wildland–urban interface. WUI-NITY, use real-time information and incorporates three layers during a wildfire i.e., evacuation and pedestrian and traffic movement.

Further works (Butler and Forthofer, 2002), (Butler and Cohen, 1998) highlight the significance of safety zones for firefighter safety during fire suppression operations. According to the authors, safety zones should adhere to the 4 times flame height rule for optimal firefighter protection.

Table 35 provide further details regarding the variables used in the selected models for evacuation route planning and safe zone estimation.

Table 35: Description of variables for selected models used for evacuation route planning and safe zone estimation.

Model Name	Model	Mathematical Expression	Input Variable	Description of Variable	Type	Range
M72-EP.1	Wang et. al. (2014)	Modified A* Algorithm	SN	Start node of the graph		
			DN	Destination node		
			VS	Speed of vehicle	Numerical	Float
			DT	Departure time	Datetime	YYYY-MM-DD-HH:MM:SS, Y: Integer, M: [1, 12], D: [1, 31], H: [0, 23], M: [0, 59], S: [0, 59]
			Tclosednini+1			
M72-EP.2	Wang and Zlatanova (2020)	Modified Dijsktra's Algorithm	SN	Start node of the graph		
			DN	Destination node		
			VS	Speed of vehicle	Numerical	Float
			DT	Departure time	Datetime	YYYY-MM-DD-HH:MM:SS, Y: Integer, M: [1, 12], D: [1, 31], H: [0, 23], M: [0, 59], S: [0, 59]

			Tmax	Time constraint for passing through an edge	Float	>= 0s
M72-EP.3	Kuligowski (2021)	-	-	-	-	-
M72-EP.4	Beloglazov et. al. (2016)	Dijkstra’s Algorithm				
M72-EP.5	WUI-NITY	Itinero API (based on Dijkstra)				
M72-SZ.1	Butler and Forthofer (2002)	4*max{Fh} + sqrt((Aff*Nff + Ae*Ne)/3)	Fh	Flame Height	Numeric	>= 0.0 m
			Aff	Area needed for each firefighter	Numeric	>= 1.0 m^2
			Nff	Number of firefighters in the safe zone	Numeric	>= 1 firefighter
			Ae	Area needed for each item/ heavy equipment	Numeric	>= 1.0 m^2
			Ne	Number of items/ heavy equipment	Numeric	>= 1 firefighter
M72-SZ.2	Butler and Cohen (1998)	4*max{Fh}	Fh	Flame Height	Numeric	>= 0.0 m

2.16.2.3 Assessment of relevant models

A summary assessment of important models dealing with evacuation route planning and safety zone estimation is provided in appendix 5.11 (Table 62 and Table 63).

2.16.3 Relevant tools

2.16.3.1 Overview of relevant tools

Table 36 provides an overview of tools used for evacuation route planning.

Table 36: Overview of tools for evacuation route planning.

Tool Code	Tool Name	Installability	Applicability	Main Capabilities	Main Restrictions	Integrated Models
T72-EP.1	Openrouteservice	Web API, Python <= 3.7	Phase B	Can estimate shortest or fastest path for multiple modes (walking, driving etc). Can estimate multiple paths. Open Source.	Maximum of 3 possible routes, cannot estimate safest route	
T72-EP.2	EscapeWildFire	Windows 10 or higher, MacOS, Linux, Android	Phase B	Uses ForeFire solver to compute the fire spread simulation. Based on the results, it finds all possible routes from different maps and maps to them a score for safety and risk.	Poor scalability, lack of response time, manually add location and ignition of fire (e.g. doesn't use sensors or drones), complex scenarios, support for peaple with disabilities, real-time route changes, less accurate fire prediction model.	
T72-EP.3	waze	Moblile Application. Android (Android: OS 7 and above). iPhone (iOS: 14 and above)	Phase B	Can create real-time traffic alerts. Can provide alternative Routes. Can genarete community-Based reports. free of charge	Battery Drain, Data usage	
T72-EP.4	OpenStreetMap	Web API, integrated with multiple frameworks	Phase B	Visualization of every route in the area, integration with many apps/tools, open source, custom maps	Cannot estimate safest route	
T72-EP.5	Google Maps API	Web API, integrated with multiple frameworks	Phase B	Visualization of every route in the area, integration with many apps/tools, custom maps, optimized route selection	Cannot estimate safest route	

T72-EP.6	A* Algorithm	Algorithmic formula	Phase B	Heuristic algorithm for calculating the minimum cost path	Lack of route's safety estimation	M72-EP.1
T72-EP.7	Dijkstra's algorithm	Algorithmic formula	Phase B	Mathematical algorithm for calculating the minimum cost path	Lack of route's safety estimation	M72-EP.2 M72-EP.4
T72-EP.8	IBM Evacuation Planner	Not Enough Informations	Phase B	Multi-model system SaaS, Ignition points, wind speed and direction, fire danger index, shelters / evacuation centres	Cannot estimate safest route, closed-source	M72-EP.4
T72-EP.9	Simulation of Urban Mobility (SUMO)	Windows 10, Linux, MacOS, python >= 3.6	Phase B	Traffic simulation package, Routing, Open Source	Cannot estimate safest route	M72-EP.4
T72-EP.10	MASON	Java Development Kit (JDK) >= 8.0	Phase B	Multiagent simulation toolkit, No domain-specific features	Cannot estimate safest route	M72-EP.1, M72-EP.2
T72-EP.11	GeoMASON	Java Development Kit (JDK) >= 8.0	Phase B	Vector and raster geospatial data	Cannot estimate safest route, cannot simulate traffic, cannot estimate departure time	M72-EP.2
T72-EP.12	Unity	Windows 7, MacOS, Ubuntu 18.04, Ubuntu 20.04, X64 architecture with SSE2 instruction set support, DX10	Phase B	Game development engine	Doesn't provide ready traffic simulations, safest route estimations, departure time estimations	M72-EP.5
T72-EP.13	Gridded Population of the World (GPW)	Web Access	Phase B	Online Database, modelled the distribution of human population	Doesn't provide ready traffic simulations, safest route estimations, departure time estimations	M72-EP.5
T72-EP.14	WISE platform	Web GIS, not clear which one		Wildfire, Egress, Evacuation Planning, web-gis, platform		M72-EP.7

2.16.3.2 Description of relevant tools

The evacuation route planning tools are concisely presented in the following paragraphs.

T72-EP.1 Openrouteservice

OpenRouteService.org is an online platform designed to help users find routes between two locations, allowing the inclusion of intermediate waypoints and obstacle avoidance. It offers two criteria for route selection: the shortest distance and the fastest time. OpenRouteService uses static data and provides routing for cars, bicycles, and trucks, while also serving pedestrian movement.

T72-EP.2 EscapeWildFire

EscapeWildFire is a framework and a mobile application which models and predicts wildfire geographical progression, assisting citizens to escape wildfires in real-time (Kamilaris, et. al. 2023).

T72-EP.3 waze

Waze (Galeso M., 2016) is one of the most well-known GPS navigation applications, and it is also free to use. Its main distinction from other navigators is its real-time updates on traffic, roadworks, accidents, available parking spaces, and more. Additionally, Waze provides information about the cheapest gas stations along your route and its new feature (beta version) could help drivers avoid the most dangerous roads.

T72-EP.4 OpenStreetMap

OpenStreetMap (Haklay & Weber 2008) is a map with an open license, collaboratively developed by a global community of volunteers. These dedicated individuals contribute to data regarding roads, pathways, cafes, railway stations, and various other features across the globe. OpenRouteService makes use of open data from OpenStreetMap, where maps covering the entire globe are collaboratively created by teams of cartographers.

T72-EP.5 Google Maps API

Google Maps API allows developers to access Google Maps data and functionality for their own projects (Svennerberg, 2010).

T72-EP.6 A* algorithm

A* algorithm (Hart et. al., 1968) is a mathematical-heuristic algorithm for calculating the shortest path in a weighted graph, taking into account both the cost of reaching the goal and the estimated distance from the current node to the goal (heuristic). It combines some aspects of Dijkstra's algorithm and greedy best-first search. This is the general algorithm and not a software or program tool.

T72-EP.7 Dijkstra's algorithm

Dijkstra's graph algorithm (Dijkstra, 1959) is a mathematical algorithm for finding the shortest path from a single source node to all other nodes in a weighted graph. It uses a greedy approach, iteratively exploring nodes with the smallest cumulative distance from the source until all reachable nodes are visited. The algorithm is effective for non-negative edge weights. This is the general algorithm and not a software or program tool.

T72-EP.8 IBM Evacuation Planner

IBM Evacuation Planner is a multi-model system SaaS that facilitates in-depth exploration of hypothetical bushfire situations, enabling users to evaluate the impact of such events on different scales, ranging from large areas to individual levels. Additionally, the tool's scenario building capabilities allow users to measure and compare the effectiveness of various strategies for mitigating risks.

T72-EP.9 Simulation of Urban Mobility (SUMO)

SUMO (Behrisch et. al., 2011) is a freely available, detailed, multi-modal traffic simulation tool. Through this, users can simulate the movement of individual vehicles from a specified traffic demand within a given road network. It contains lots of capabilities of traffic management subjects. The simulation is entirely microscopic, meaning that each vehicle is represented explicitly with its own designated route, allowing them to move independently throughout the network.

T72-EP.10 MASON Multi-Agent Simulation Toolkit

MASON (Cioffi et. al., 2005) is a fast agent-based simulation library core in Java, designed to be the foundation for large custom-purpose Java simulations, and also to provide more than enough functionality for many lightweight simulation needs. MASON contains both a model library and an optional suite of visualization tools in 2D and 3D.

T72-EP.11 GeoMASON

GeoMASON (Sullivan et. al., 2010) is an extension of T72-EP.10 MASON that provides geospatial support. It adds support for vector and raster geospatial data. With GeoMason one is able to load, display, and manipulate data that is grounded to the Earth’s surface.

T72-EP.12 Unity

Unity is a powerful and widely-used game engine. With its user-friendly interface and a vast array of tools, it is used, not only by game developers, but by researchers for advanced modeling and simulations. Given its modularity, there are different submodels for each traffic mode that can be replaced with different models.

T72-EP.13 Gridded Population of the World (GPW)

GPW is an online collection of the human population distribution over the globe. Its purpose is to provide a spatially disaggregated population layer that is compatible with data sets from social, economic, and Earth science disciplines, and remote sensing. It provides globally consistent and spatially explicit data for use in research, policymaking, and communications.

Table 37 presents the main variables of each tool used for evacuation route planning.

Table 37: Description of variables for the evacuation rote planning tools.

Tool Name	Tool	Purpose	Input Variable	Description of Variable	Type	Range
T72-EP.1	OpenRouteService	K-Fastest/Shortest Routes Estimation, based on a modified Dijkstra's algorithm.	[(P1.x, P1.y), (P2.x, P2.y) …]	Coordinations of the start and end points	Numeric	Pi.x: [-90.0, 00.0], Pi.y: [-180.0, 180.0]
			alternative_routes	Number of K alternative routes	Numeric	[1, 3]
T72-EP.2	EscapeWildFire	Simulates fire spread and returns all possible paths, sorted by safety and risk	**Lf**	Location of fire	Numeric	Lf.x: [-90.0, 90.0], Lf.y: [-180.0, 180.0]
			Ti	Time of ignition	Datetime	YYYY-MM-DD Y: integer M: [1, 12] D: [1, 31]
			M	Mode of transport	Categorical	{"car", "bike", "foot"}
			N	Navigation method	Categorical	{"turn-by-turn", "direction-based"}
T72-EP.3	Waze	Mobile application for navigating inside traffic	V	Vehicle	Categorical	{"Private Use", "Taxi", "Motorcycle"}
			D	Destination	Categorical	
			F	Fuel Type	Categorical	{"Unleaded 95", "Unleaded 100", "Diesel", "LPG"}
			TS	Traffic Sign	Numeric	[0, 99]
			TL	Tolls and Licenses	Categorical	{"London C Charge Exempt", "London ULEZ Compliant", "M-flow", …}
			AT	Avoid Tolls	Boolean	True/False
T72-EP.4	OpenStreetMap	Geographical data and tools integration for custom maps	L	Location	Categorical	
			P	Coordinates	Numerical	P.x: [-90.0, 90.0], P.y: [-180.0, 180.0]
T72-EP.5	Google Maps API	Geographical data and tools integration for custom maps.	L	Location	Categorical	
			P	Coordinates	Numerical	P.x: [-90.0, 90.0], P.y: [-180.0, 180.0]

2.17 M82: Models for soil erosion

2.17.1 *Introduction*

Soil erosion is a global environmental problem influenced by both natural and human factors and encompasses a broad range of processes that involve soil detachment and transport due to forces that act upon Earth surface. Remote sensing and field-based geospatial technology provides effective tools for detecting and mapping specific landforms that are created by different driving forces:

- soil erosion by overland flow (sheet, rill, gully),
- channel erosion by fluvial processes,
- gravitational erosion, landslides, debris flow,
- wind erosion,
- coastal erosion by surge and waves,
- glacial erosion.

Soil erosion is aggravated by abrupt climate variability, exploitation of natural resources, land degradation, etc. As a result, soil erosion and its environmental consequences are growing concerns worldwide (Gilani et al., 2022; Tsesmelis et al., 2022). Over the last few decades, it has become increasingly clear that soil erosion poses a significant risk to long-term soil sustainability, leading to soil management scenarios and practical conservation practices to preserve soil against erosive forces (Telak et al., 2021; Tesfahunegn et al., 2021; Khalil and Aslam, 2022).

Geospatial information science (GISc)-based analysis and modeling plays an important role in integrating observations and models, and improves understanding and prediction capabilities aimed at minimizing negative impacts of erosion and sedimentation.

2.17.2 Relevant models

2.17.2.1 Overview of relevant models

Modeling provides a quantitative and consistent approach to estimate soil erosion and sediment yield under a wide range of conditions and is needed to guide the comprehensive control of soil erosion. Over the years various soil erosion models have been developed. The application of these models is dependent on the soil type and climate of the given area because models differ in complexity and input requirements.

Erosion modeling is used in order to achieve a better understanding of erosion processes, provided that experimental conditions from which directly measured outcomes could be derived, are either impossible or impractical to create (Tolk, 2015). The importance and achievements of erosion modelling (either for soil loss, sediment yield, or both) have been argued by a plethora of research works.

The wide spreading of geographic information systems (GIS) and use of remote sensing data has accelerated erosion model development significantly, as it allows for data input from multiple sources, easy model structure modifications, and unconditioned model rescaling (Giordano et al., 1991; De Vente and Poesen, 2005). According to Karydas et al. (2014), more than 80 erosion models have been developed for different purposes in half a century. Despite the wealth of erosion models and applications, though, the selection of an appropriate model for operational mapping remains a difficult undertaking.

Erosion modeling is based on an understanding of physical laws and relief modeling procedures. Modeling translates these components into mathematical relationships, describing the fundamental processes of erosion, runoff, detachment, transport, and deposition (Jetten et al., 2003).

In general, models fall into three main categories, depending on the physical processes they simulate and the equations they use to describe those processes (Hajigholizadeh et al. 2018). These categories of models are:

(1) Empirical models,

(2) Conceptual models,

(3) Physically-based models.

Empirical Models

According to Wheater et al (Wheater et al., 1993) empirical models are a simulation of natural processes, mostly based on statistical relationships. The mathematical models are simple, and their data requirements are less than those that are required for the other model categories. In this way. The main drawback of this kind of model is that they are valid mainly for the geographical area where they are made for. Empirical models also ignore the heterogeneity of some catchments as it is rainfall and soil types. Moreover, due to their simplicity, this kind of model usually ignores the non-linear relationships between the variables in a catchment system.

The simplicity, of empirical models makes them useful in cases there is a limited set of data and also the lack of a requirement for complex inputs. In such cases, they can be considered preferable to more complex and demanding. Empirical models are valuable as a first step in identifying sources of sediment and nutrient generation.

Conceptual Models

Conceptual models are a combination of empirical and physically based models. The main scope of the conceptual model is to estimate the sediment yield. Conceptual models represent a catchment, which incorporates the physical processes of runoff and sediment transport. This type of model usually unifies various catchment processes without specifying the process of interactions which would make it require very detailed catchment information. These models estimate the whole quantitative and qualitative effect of land use changes within a watershed, without taking into consideration the spatial and temporal variability.

The value of each parameter in conceptual models is obtained through calibration using real observations, such as discharge and sediment concentration]. Simple conceptual models tend to have fewer problems with model identification than complex models.

Physically-Based Models

Physically-based models are based on the physical lows of the conservation of mass, momentum equations, and energy as governing equations for streamflow or overland flow, and conservation of mass equation for sediment yield (Kandel et al., 2004). Most of the developed physically-based soil erosion models in use are not pure physically-based but the mathematical expressions describing the individual process are based on empirical or conceptual approaches (Pandey et al., 2016).

Physically-based models, in particular, are usually over-parametrized due to the existence of a large number of complex parameters (Wheater et al. 1993). This procedure creates extra uncertainties in parameter values. In this situation, with a large number of parameter values (in some cases, hundreds) that are required to be measured through the mentioned process, the ability to identify the model parameters will become very difficult, and the non-uniqueness of 'best fit' solutions can be expected (Beck et al. 1987).

Because of the complexity of some composite models (physically-based, conceptual or hybrid), in the current state of the art, they are used mainly for research purposes. For this reason, in the next, they are not presented the equations of these models' but is given a short description of the most significant of them in terms of recognition by the scientific community. Moreover, an assessment of the models and their corresponding software tools are evaluated based on the literature (Raza et al., 2021; Kanito & Feyissa, 2021; Hajigholizadeh et al., 2018; Igwe et al., 2017; Avwunudiogba & Hudson, 2014; Merritt et al., 2003).

2.17.2.2 Description of relevant models

In what follows, soil erosion models are presented.

M82.1. Universal Soil Loss Equation (USLE) - [Wischmeier and Smith, 1978]

The Universal Soil Loss Equation (USLE) predicts the long-term average annual rate of erosion on a field slope based on rainfall pattern, soil type, topography, crop system and management practices. USLE only predicts the amount of soil loss that results from sheet or rill erosion on a single slope and does not account for additional soil losses that might occur from gully, wind or tillage erosion.

M82.2. Revised Universal Soil Loss Equation (RUSLE) - [Renard et al., 1991, 1994, 1996]

The Revised Universal Soil Loss Equation (RUSLE) is an upgrade of USLE that is land use independent. It can be used on cropland, disturbed forestland, rangeland, construction sites, mined land, reclaimed land, military training grounds, landfills, waste disposal sites, and other lands where rainfall and its associated overland flow cause soil erosion.

M82.3. Modified Universal Soil Loss Equation (MUSLE) – [Williams, 1975]

The MUSLE is used within hydrological models to estimate sediment yields from catchments of various sizes, but the spatial scale dependency issues associated with estimating the MUSLE parameters have not been adequately addressed. In the absence of detailed observed data on both hydrological response and sediment yield, some analytical approaches and hypothetical examples are presented to identify the key issues. The results suggest that methods used to estimate both the erosivity and topographic factors are scale-dependent, particularly if a lumped or semi-distributed modelling approach is used.

M82.4. G2 [Panagos et al., 2012]

G2 is an empirical model for soil erosion rates on month-time intervals and has evolved with time into a quantitative tool with two distinct modules: one for soil loss and one for sediment yield.

The module for soil loss (denoted as G2los) inherits its main principles and many of its formulas from the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and the Revised-USLE (RUSLE) (Renard et al., 1997). Ferro and Porto (2010) argue that USLE is a robust empirical model with a logical structure regarding the variables used to simulate the physical erosion process. The input datasets of the G2 applications can be derived from geodatabases freely and regularly available by European or other international institutions.

The module for sediment yield (denoted as G2sed) adopts the sediment delivery ratio (SDR) formula from the Erosion Potential Method (EPM) (Gavrilovic, 1988, da Silva et al., 2014). The main input dataset is a high-resolution digital elevation model (DEM), from which the required topographic and hydrographic properties can be derived. The G2sed module uses the outcome of the G2los module and the calculated EPM figures, to produce sediment yield maps (Karydas and Panagos, 2016).

M82.5. USPED (Unit Stream Power - based Erosion Deposition) – [Mitasova et al., 1996; Mitas and Mitasova, 1998]

USPED (Unit Stream Power - based Erosion Deposition) is a simple model which predicts the spatial distribution of erosion and deposition rates for a steady state overland flow with uniform rainfall excess conditions for transport capacity limited case of erosion process. The model is based on the theory originally outlined by Moore and Burch 1986 with numerous improvements.

M82.6. WaTEM/SEDEM model – [Van Oost et al., 2000; Van Rompaey et al., 2001]

WaTEM/SEDEM was applied to simulate soil loss and deposition rates at the European scale.

The long-term annual rates of soil loss, sediment transfer and deposition were modelled with WaTEM/SEDEM. The model has been extensively employed to estimate net fluxes of sediments across landscape, catchment- and regional-scale level.

M82.7. Gavrilovic (Erosion Potential Method, (EPM) – [Gavrilovic, S., 1962, 1970, 1972]

The Gavrilović method (Erosion Potential Method, EPM) is an empirical, semiquantitative model (Gavrilović 1972). The method was based on erosion field research in the Morava River catchment area in Serbia and encompasses erosion mapping, sediment quantity estimation, and torrent classification. Since 1968, the method has been extensively applied to erosion and torrent-related problems in the Balkan countries.

M82.8. Koutsoyiannis and Tarla – [Koutsoyiannis and Tarla, 1987]

This study is an attempt to draw conclusions from the available sediment measurement data in Greece and includes: (a) a brief report on the regime of sediment measurements in Greece, as well as their processing and utilization; (b) investigation of the effects of hydrological, climatic, topographical and geological factors on the sediment yield, based on the gauged data of Northwestern Greece with an attempt to interpret the effect of these factors; (c) derivation by statistical methods of an empirical formula for the sediment yield estimation from hydrological and geological data of the watershed.

M82.9 ART model [Syvitski et al., 2003]

The Syvitski et al. (2003) model, comprising two individual equations, was developed based on field data deriving from 340 different catchments scattered across the globe. The equations were created taking into account geomorphological data, sediment measurements and a mean annual temperature estimation method.

The ART model has a better fit to observations for certain climate zones (Syvitski et al., 2003) and pro-vides a convenient, powerful tool for sediment discharge prediction, it is necessary to weigh model accuracy against model complexity (i.e., the number of free parameters in the model) when evaluating model performance. As the number of free parameters of any model grows, the root-mean-square (RMS) error of that model tends to decrease whether or not the model with more free parameters is actually a better representation of the physical processes at work in the system compared to a model with fewer free parameters.

M82.10. BQART model [Syvitski and Milliman, 2007]

Syvitski and Morehead (1999) employed dimensional analysis to the problem of predicting a river basin's long-term sediment load, concentrating on the parameters Qs [M/T], A [L2], R [L], fluid density ρ [M/L3], and gravity g [L/T2].

2.18 M83: Geomorphological and topographic models for sediment yield and discharge

2.18.1 Introduction

Sediment Yield and Discharge are two important concepts in hydrology, geomorphology, and environmental management, particularly in the context of river systems, watershed management, as well as erosion. The following section describes geomorphological and topographic models that are relevant for sediment yield and discharge.

2.18.2 Relevant models

M83.1. Dendy and Bolton [Dendy and Bolton, 1976]

Dendy Bolton formula, (1976) is used to determine the sediment yield of all types of erosion such as sheet and rill Erosion, gully Erosion, channel Bed and bank erosion and mass movement. Area of watershed by Arc GIS and Runoff of the basin is used to determine sediment yield in the Dendy Bolton method.

Their individual factors do not display annual variation. Additionally, they oversimplify the complex erosion processes that correlate sediment yield or discharge only with the basin area.

M83.2. Avendano Salas et al. [Avendano Salas et al., 1997]

Avendaño Salas et al. (1997) published a database with mean annual sedimentation rates for the 60 Spanish reservoirs. The reservoirs are distributed all over Spain, in various climatic, geologic and geomorphologic regions of the country, with a concentration along the relatively dry Mediterranean coast but without representation of the relative humid Northwestern area.

M83.3. Lu et al. [Lu et al., 2003]

The Lu et al. (2003) equation was developed based on sediment discharge data from 248 gauging sites in the Upper Yangtze basin in China.

M83.4. Webb and Griffiths [Webb and Griffiths, 2001]

Webb and Griffiths (2001) developed an equation for the estimation of mean annual sediment discharge based on data from 37 catchments in northern Arizona.

M83.5. Mulder and Syvitski [Mulder and Syvitski, 1996]

Frequency of hyperpycnal plumes emanating from river discharge can be predicted with knowledge of rating curve characteristics, particularly during flood conditions. Examples of these curves are shown for middle-sized North American rivers. Semi-empirical relationships among average discharge, average sediment concentration, and the discharge during flood are proposed and applied to 150 world rivers. Results show the importance of small and medium sized rivers in their ability to trigger underflow at their mouth.

M83.6. Geomorphological - Topographic models – [Lykoudi & Zarris 2004; Zarris et al. 2007]

Geomorphological models, comprising two individual equations, was developed based on field data from 11 watersheds located in northwestern Greece. The equations attempt to correlate the suspended sediment yield and discharge with geological and morphological parameters.

An attempt is made to correlate the suspended sediment estimates mainly with geomorphologic parameters, which rarely has been carried out in the international literature. Correlation of mean annual sediment yield with the Hypsometric Integral (HI), Bifurcation Ratio (RB), USLE Soil Erodibility Factor (K), Catchment length (Lbmax), Maximum catchment elevation (Hmax), Drainage Density of the stream network (DD).

The main disadvantage of the aforementioned approximations is the fact that they can only attribute numerical values without being able to identify the high-risk erosion areas (the parameters used do not display spatial distribution.

2.19 M84: Soil erosion models focused on hydraulics

2.19.1 Introduction

Soil erosion models related to hydraulics focus on understanding and predicting how water movement can cause soil erosion. Two of the most commonly used models are presented in the following. Moreover, some additional well-known models are presented, which are of composite nature (i.e., physically based, conceptual and hybrid), which makes them complex and sometimes difficult to apply in practice.

2.19.2 Relevant models

Models that are simpler (non-composite) mainly include the following:

M84.1. Conceptual (semi- Empirical)-based models/Revised Morgan-Morgan-Finney (RMMF) [Morgan et al., 1984; Morgan, 2001, 2005]

The RMMF model separates the soil erosion process into two phases: the water phase and the sediment phase. The water phase determines the energy of the rainfall available to detach soil particles from the soil mass and the volume of runoff. In the erosion phase, rates of soil particle detachment by rainfall and runoff are determined along with the transporting capacity of runoff (Morgan, 2001).

M84.2. Physically-based models/indices Hydraulics [sediment discharge rating curves, runoff (Q) - sediment discharge (Qs) curves] – [Koutsoyiannis, 2000; Zarris, et al. 2002]

The broken line smoothing *Q-Qs,* was introduced by Koutsoyiannis (Koutsoyiannis & Tarla, 1987), as a simple alternative to numerical smoothing and interpolating methods and is treated here as a replacement for the ordinary single rating curve. The broken line is a concatenation of straight-line segments, where the number of the straight-line segments is numerically the outcome of the compromise between the two objectives of minimizing the fitting error and the roughness of the broken line. Considering that the prevailing fluvial form is the gravel-bed river form, we assume a broken line with two segments. In such a fluvial form, there is a distinct threshold discharge for sediment motion. Below this threshold there is no exchange of the suspended sediment with the riverbed. Once the surface, coarse material, armor layer fully breaks up beyond the threshold discharge and exposes a larger range of particle sizes underneath, the transport rate significantly increases. Alternatively, bank erosion during high discharges will enhance the sediment availability in the riverbed.

On the other hand, composite models include the following:

M84CM.1. Physically - based models/Aerial Non-Point Source Watershed Environment Response Simulation (ANSWERS)- [Beasley et al., 1989]

The ANSWERS model developed by Beasley et al. (1989) is a fully spatially distributed for catchment erosion and sediment yield model assessment. It is based on the water erosion and sediment transport model. The main component of the model is the sediment continuity equation of Foster et al., (1977), and the conceptual basis for the water routing model was taken from Nearing et al. (1994). The ANSWERS project assesses the effects of land use, management schemes and agricultural, practices on soil erosion and sentiment yield.

M84CM.2. Physically -based models/AGWA – [Goodrich et al. 2011]

The Automated Geospatial Watershed Assessment (AGWA) tool facilitates parameterization and calibration of the model. AGWA uses internationally available spatial datasets to delineate the watershed, subdivide it into model elements, and derive all necessary parameter inputs for each model element. AGWA also enables the spatial visualization and comparison of model results, and thus permits the assessment of hydrologic impacts associated with landscape change. The utilization of a GIS further provides a means of relating model results to other spatial information.

M84CM.3. Physically-based models/Chemical, Runoff and Erosion from Agricultural Systems (CREAM) [Knisel, 1981]

CREAMS is a field-scale (less than 5 ha in size) model that predicts runoff, erosion and chemical transport from agricultural areas. The model was developed as a tool to evaluate the effects of various agricultural practices on pollutants in surface runoff and in soil water below the root zone, in response to off-site water quality concerns. It operates in both single storm events and in a long-term average (continuous) mode. The continuous mode is the intended mode of operation, and it can predict long-term averages from two to 50 years.

M84CM.4. Physically-based models/Griffith University Erosion System Template (GUEST) – [Beasley et al., 1989; Dabral and Cohen, 2001]

Excluding gully processes and mass movement, the rate of erosion of bare soil depends on the rate of overland flow and rainfall, on the erodibility and desirability of surface soil, and on the features of filling if this occurs. The program GUEST is designed to analyze data collected from runoff plots of simple form', and to yield an approximate non-dimensional erodibility parameter denoted by β. The parameter β has a theoretical basis and is more physically meaningful if flow-driven erosion processes dominate those due to rainfall impact.

M84CM.5. Physically-based models/Erosion Productivity Impact Calculator (EPIC) [Sharpley and Williams, 1990]

Beginning in 1981, a mathematical model called the erosion-productivity impact calculator model (epic) was developed to determine the relation between soil erosion and soil productivity throughout the U.S.A.

M84CM.6. Physically-based models/Water Erosion Prediction Project/ WEPP [Foster and Lane, 1987; Lane and Nearing 1989]

The WEPP model (Nearing et al., 1989) was intended to replace the USLE family models and expand the capabilities for erosion prediction in a variety of landscapes and settings. It is a physically based model with distributed parameters that can be used in either a single event or continuous time scale and calculates erosion from rills and inter-rills, assuming that detachment and deposition rates in rills are a function of the transport capacity.

M84CM.7 Conceptual-based models/Agricultural Non-Point Source Pollution (AGNPS) [Young et al., 1987, 1989, 1994]

Agricultural Non-Point Source Pollution Model (AGNPS) is a joint USDA - Agricultural Research Service (ARS) and - Natural Resources Conservation Service system of computer models developed to predict nonpoint source pollutant loadings within agricultural watersheds.

M84CM.8. Conceptual-based models/IHACRES-WQ – [Jakeman and Hornberger, 1993]

The IHACRES model (Identification of unit Hydrographs and Component flows from Rainfall, Evaporation, and Streamflow data), a conceptual rainfall-runoff model based on metric calculations, is available as a module library. This model uniquely operates without the need for spatial data like elevation models, or soil and land use maps. It has been successfully utilized across various catchments, accommodating a diverse array of sizes and climatic conditions.

M84CM.9. Physically-based models/Limburg Soil Erosion Model/ LImburg Soil Erosion Model (LISEM) – [de Roo et al., 1996; de Roo και Jetten, 1999]

The Limburg Soil Erosion Model (LISEM) (de Roo et al., 1996; de Roo and Jetten, 1999) is a distributed physically based hydrological and soil erosion model developed for planning and conservation purposes. LISEM incorporates a number of different processes, including rainfall interception, surface storage in micro-depression, infiltration, vertical water movement through the soil, overland flow, channel flow, detachment by overland flow and transport capacity of flow. LISEM does not simulate concentrated erosion in rills and gullies; rather it simulates flow detachment only in the ponded area. This can be seen as intermediate between sheet and rill erosion. Processes describing sediment detachment by rainfall, throughfall and overland flow are included, in addition to the transport capacity of the flow.

M84CM.10. SWAT model – [Arnold et al., 2012; Kavian et al., 2017]

The Soil and Water Assessment Tool (SWAT) I (Arnold and Fohrer, 2005). The equations are formulated for use with continuous spatial and temporal data, yet the data used in practice are often point source data to represent, for example, an entire unit area in the catchment. The viability of lumping up small-scale Physically to the scale of the spatial grid used in many physically based models is questionable. Nearing et al. (1994) state that model parameters derived in this manner represent nothing more than fitted coefficients distorted beyond any physical significance. The use of small-scale parameters in small- scale models may lose physical significance at larger scales. Specifically, there is a lack of theoretical justification for assuming that equations apply equally well at the grid scale at which they are representing the lumped aggregate of heterogeneous sub-grid processes.

M84CM.11. Simulator for Water Resources in Rural Basins (SWRRB) [Williams et al., 1985]

A model called SWRRB (Simulator for Water Resources in Rural Basins) was developed for simulating hydrologic and related processes in rural basins. The objective of model development was to predict the effect of management decisions on water and sediment yields with reasonable accuracy for engaged rural basins throughout the United States. The three major components of SWRRB are weather, hydrology, and sedimentation. Processes considered include surface runoff, percolation, return flow, evapotranspiration, pond and reservoir storage, and sedimentation.

2.19.3 Overview of soil erosion models

Table 38 provides an overview of the models presented in chapters 2.17-2.19, i.e. models related to soil erosion (including also geomorphological and topographic models, as well as hydrological models), along with their main variables.

Table 38: Overview of models related to soil erosion (along with their variables), including also geomorphological and topographic models, as well as hydrological models.

Model Name	Model/Reference	Mathematical expression	Variable	Description	Type	Range	Verbal
M82.1 **USLE** **Type:** Conceptual (Empirical)-based models /Universal Soil Loss Equation (USLE) **Application scale:** slope/sub-basin **Time scale rain:** event /annual **Output:** erosion	**(Wischmeier and Smith, 1978)**	$A = R \times K \times LS \times C \times P$	A	Mean annual soil loss per unit of area (t ha^{-1} y^{-1})	Numeric (2,3)	>0,0	
			R	Rainfall erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1})	Numeric (2,3)	>0,0	
			K	Soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1})	Numeric (2,3)	>02	
			LS	Topographic factor (dimensionless) which incorporates the individual slope length (dimensionless) and slope steepness (dimensionless) factors	Numeric (2,3)	>0,0	
			C	Mean annual soil loss per unit of area (t ha^{-1} y^{-1})	Numeric (2,3)	>0,0	Tabulated values per cover type/ crop stage period
			P	Same as M82.2			Tabulated values per conservation technique
	Variables (1st level)	$LS = \left(\frac{\lambda}{72.6}\right)^{m} (65.41 \sin^2 \theta + 4.56 \sin \theta + 0.065)$	λ	Slope length (ft)	Numeric (2,3)	>15	
			m	Exponent (dependent on the slope)	Numeric (2,3)/ Jenks classes	0.2 0.3 0.4 0.5	s<1% 1%≤s<3% 3%≤s<5% s≥5
			θ	Slope angle in degrees	Numeric (2,3)		

	Variables (2nd level)	$L=\left(\frac{\lambda}{72.6}\right)^{m}$	λ	Same as Variables (1st level)			
			m	Same as Variables (1st level)			
		$S=65.41\sin^{2}\theta+4.56\sin\theta+0.065$	θ	Same as Variables (1st level)			
	Variables (3rd level)	$\sin\theta=\frac{s}{\sqrt{100^{2}+s^{2}}}$	s	slope steepness (%)	Numeric (2,3)	0-100	
M82.2 **RUSLE** **Type:** Conceptual (Empirical)-based models / Revised Universal Soil Loss Equation (RUSLE) **Application scale:** slope/sub-basin **Time scale rain:** event /annual **Output:** erosion	**(Renard et al., 1991, 1994, 1996)**	$A=R\times K\times LS\times C\times P$	A	Mean annual soil loss per unit of area (t ha^{-1} y^{-1})	Numeric (2,3)	>0,0	
			R	Rainfall erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1})	Numeric (2,3)	>0,0	
			K	Soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1})	Numeric (2,3)	>02	
			LS	Topographic factor (dimensionless) which incorporates the individual slope length (dimensionless) and slope steepness (dimensionless) factors	Numeric (2,3)	>0,0	
			C	Cover management factor (dimensionless)	Numeric (2,3)	0-1	0 (strong protection) to 1 (reference condition/ bare plot – no protection), depended on the vegetation density
			P	Conservation practice factor (dimensionless)	Numeric (2,3)	0-1	0 (strong protection) to 1 (reference condition/ bare plot – no protection),

							depended on the practices applied Tabulated values per conservation technique
	Variables (1st level)	$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{mj}(EI_{30})_k$	R	Mean annual rainfall erosivity (MJ mm ha^{-1} h^{-1} y^{-1})	Numeric (2,3)	>0,0	
			n	number of years covered by the data records	Numeric (2,3)	>0,0, integer	
			mj	number of erosive events of a given year j	Numeric (2,3)	>0,0, integer	
			EI_{30}	rainfall erosivity index of a single event k (MJ mm ha^{-1} h^{-1})	Numeric (2,3)	>0,0	
		$K = \left[\frac{(2.1M^{1.14}(10^{-4})(12-a)+3.25(b-2)+2.5(c-3))}{100}\right]0.1317$ $LS = \left(\frac{\lambda}{72.6}\right)^m \begin{cases} 10.8\sin\theta + 0.03, \lambda \geq 15ft, s < 9\% \\ 16.8\sin\theta - 0.50, \lambda \geq 15ft, s \geq 9\% \\ 3.0(\sin\theta)^{0.8} + 0.56, \lambda < 15ft \end{cases}$ $C = (SLR_1EI_1 + SLR_2EI_2 + \cdots + SLR_nEI_n)/EI_t$	M	Soil grain size parameter	Numeric (2,3)	>0,0	
			a	Soil organic matter content (%),	Numeric (2,3)	0-4	
			b	Soil structure	Numeric (2,3)	1 2 3 4	Very fine granular Fine granular Medium or coarse granular Blocky, platy, or massive
			c	Soil permeability	Numeric (2,3)	1 2 3 4 5	Rapid Moderate fast Moderate Moderate low Slow

						6	Very slow
			λ	Slope length (ft)	Numeric (2,3)	>0,0	
			m	Exponent	Numeric (2,3)	>0,0	function of the rill to inter-rill erosion ratio β
			θ	Slope angle in degrees	Numeric (2,3)		
			SLR_i	Soil Loss Ratio for the time period i			
			EI_i	Percentage of the annual or crop EI occurring during that time period			
			n	n is the number of periods used in the summation			
			EI_t	sum of the EI percentages for the entire time period			
	Variables (2nd level)	$EI_{30} = \left(\sum_{r=1}^{0} e_r v_r \right) I_{30}$	e_r	unit rainfall energy (MJ ha^{-1} mm^{-1})	Numeric (2,3)	>0,0	
			v_r	rainfall volume (mm) during a period r	Numeric (2,3)	>0,0	
		$M = P_s(100 - P_c)$	P_s	silt + very fine sand fraction (%)	Numeric (2,3)	0-70	the equation can only be used if the "silt + very fine sand" fraction is less than 70%
			P_c	clay fraction (%)	Numeric (2,3)	0-100	
		$L = \left(\frac{\lambda}{72.6} \right)^m$	λ	Same as Variables (1st level)			

			m	Same as Variables (1st level)			
		$S = \begin{cases} 10.8\sin\theta + 0.03, \lambda \geq 15ft, s < 9\% \\ 16.8\sin\theta - 0.50, \lambda \geq 15ft, s \geq 9\% \\ 3.0(\sin\theta)^{0.8} + 0.56, \lambda < 15ft \end{cases}$	θ	Same as Variables (1st level)			
			λ	Same as Variables (1st level)			
		$m = \frac{\beta}{1+\beta}$	β	rill to inter-rill erosion ratio	Numeric (2,3)	0-100	
		$SLR = PLU \times CC \times SC \times SR \times SM$	SLR	Soil Loss Ratio			
			PLU	Prior Land Use subfactor	Numeric (2,3)	0-1	
			CC	Canopy Cover subfactor	Numeric (2,3)	0-1	
			SC	Surface Cover subfactor			
			SR	Surface Roughness subfactor			
			SM	Soil Moisture subfactor			
	Variables (3rd level)	$e_r = 0.29[1 - 0.72\,exp(-0.05 i_r)]$	e_r	unit rainfall energy for each time interval	Numeric (2,3)	>0,0	
			i_r	rainfall intensity during the time interval (mm h^{-1})	Numeric (2,3)	>0,0	
		$\beta = \frac{\left(\frac{\sin\theta}{0.0896}\right)}{[3.0(\sin\theta)^{0.8} + 0.56]}$	θ	Same as Variables (1st level)			
		$PLU = C_f \times C_b \times exp\left[(-c_{ur} \times B_{ur}) + (c_{us} \times B_{us}/{C_f}^{c_{uf}})\right]$	C_f	surface-soil-consolidation factor	Numeric (2,3)	0-1	for freshly tilled conditions is 1.0
			C_b	represents the relative effectiveness of			

				subsurface residue in consolidation			
			c_{ur}	calibration coefficient indicating the impacts of the subsurface residues			
			B_{ur}	mass density of live and dead roots found in the upper inch of soil (lb acre^{-1} in^{-1})			
			c_{us}	calibration coefficient indicating the impacts of the subsurface residues			
			B_{us}	mass density of incorporated surface residue in the upper inch of soil (lb acre^{-1} in^{-1})			
			c_{uf}	represents the impact of soil consolidation on the effectiveness of incorporated residue			
		$CC = 1 - F_c \times \exp\,(-0.1 \times H)$	F_c	Fraction of land surface covered by canopy			
			H (ft)	distance that raindrops fall after striking the canopy			
		$SC = exp\left[-b \times S_p \times \left(\frac{0.24}{R_u}\right)^{0.08}\right]$	b	empirical coefficient	Numeric (2,3)	0.030-0.070 for row crops 0.024-0.032 for small grains	

						0.039 for rangeland conditions 0.050 for fields dominated by rill erosion 0.025 for fields dominated by inter-rill erosion 0.035 for typical cropland erosion	
			S_p	percentage of land area covered by residue cover			
		$SP = 100 \times [1 - exp(-a \times B_s)]$	a	ratio of the area covered by a piece of residue to the mass of that residue (acre lb^{-1})	Numeric (2,3)	Tabulated	
			Bs	dry weight of crop residue on the surface (acre lb^{-1})	Numeric (2,3)	Tabulated	
			R_u	surface roughness (in)	Numeric (2,3)	Tabulated	
		$R_u = 0.24 + [D_r \times (R_i - 0.24)]$	D_r	Roughness decay coefficient (dimensionless)	Numeric (2,3)	0-1	1.0 for a surface that has experienced no rainfall

							0.0 for a surface that has experienced extensive rainfall and has lost most of its roughness
			R_i	Initial surface roughness (in)	Numeric (2,3)		
		$D_r = exp[0.5(-0.14 \times P_t) + 0.5(-0.012 \times EI_t)]$	P_t	Total inches of rainfall since the most recent operation that disturbed the entire surface	Numeric (2,3)	>0,0	
			EI_t	Total EI amount since that same operation	Numeric (2,3)	>0,0	
		$SR = exp[-0.66(R_u - 0.24)]$	SR	surface roughness subfactor	dimensionless Surface Roughness value		
		$SM = 1 - 0.5 \times exp(-9 \times s)$	SM	sloping steepness at which contouring is most effective	Numeric (2,3)	0-1	When the soil profile is at or near field capacity, SM is 1.0 (indicating response equivalent to that of a continuous-fallow plot) When the profile is near wilting point to a 6-ft depth, the SM value is 0 (indicating that no runoff and erosion are expected)
			s	plotting slope			

M82.3 **MUSLE** **Type:** Conceptual (Empirical)-based models / Modified Universal Soil Loss Equation (MUSLE) **Application scale:** slope/sub-basin **Time scale rain:** event /annual **Output:** erosion	**(Williams, 1975)**	$Y = 11.8 \times (Q \times q_p)^{0.56} \times K_{USLE} \times LS_{USLE} \times C_{USLE} \times P_{USLE}$	Y	Sediment yield to the stream network (t)	Numeric (2,3)	>0,0	
			Q	Runoff volume from a given runoff event (m^3)	Numeric (2,3)	>0,0	
			q_p	peak flow rate ($m^3\ s^{-1}$)	Numeric (2,3)	>0,0	
			K_{USLE}	Same as M82.1			
			LS_{USLE}	Same as M82.1			
			C_{USLE}				C-factor is recalculated every day that runoff occurs. It is a function of above-ground biomass, residue on the soil surface, and the minimum C-factor for the plant.
			P_{USLE}	Same as M82.1			
	Variables (1st level)	$Q_d = \begin{cases} 25.4\dfrac{(R/25.4 - 0.2S)^2}{(R/25.4 + 0.8S)}, & R > 0.2S \\ 0, & R \leq 0.2S \end{cases}$	Q_d	runoff depth (mm)	Numeric (2,3)	>0,0	After the user specifies the rainfall amount, Q_d will be calculated and then multiplied by the area to get runoff volume Q for each cell.
			R	event rainfall (mm)	Numeric (2,3)	>0,0	
			S	potential retention parameter (inch)	Numeric (2,3)	>0,0	Related to the soil and land cover conditions of the watershed
		$q_p = q_u A Q_d F_p$	q_u	Unit peak discharge ($m^3\ s^{-1}\ km^{-2}\ mm^{-1}$)	Numeric (2,3)	>0,0	

			A	Drainage area (km^2)	Numeric (2,3)	>0,0	
			Q_d	runoff depth (mm)	Numeric (2,3)	>0,0	
			F_p	Pond and swamp adjustment factor (% of pond and swamp area over the watershed area)	Numeric (2,3)	0-100	
	Variables (2nd level)	$S = 1000/CN - 10$	S				
			CN	Curve number	Numeric (2,3)		In GIS, CN can be derived from soil HSG (Hydrologic soil group) classification and land cover type (NRCS, 1986)
		$q_u = 10^{(C_0 + C_1 logT + C_2 (logT)^2)}$	C_0, C_1, C_2	Coefficients	Numeric (2,3)		Available from the Urban Hydrology for Small Watersheds manual (NRCS, 1986). They are determined by rainfall type and the ratio of initial abstraction (I_a) and 2-year 24-h rainfall (P).
	Variables (3rd level)	$T = T_t sheet + T_t shallow$	T	Concentration time (hr)	Numeric (2,3)	>0,0	
		$T_t sheet = \frac{0.091(nL)^{0.8}}{J^{0.5} S^{0.4}}$	$T_t$sheet	Travel time for sheet flow (hr)	Numeric (2,3)	<91.4m	Flow over plane surfaces and usually occurs in the headwater of streams

			n	Manning's roughness coefficient	Numeric (2,3)		
			L	flow path length (m)	Numeric (2,3)	>0,0	
			S	Slope (%)	Numeric (2,3)	0-100	
			J	2-year, 24-h rainfall (typical 24-h duration precipitation with a 2-year return period) (mm)	Numeric (2,3)	>0,0	Published by the National Weather Service (NWS)
		$T_t shallow = \frac{3.281 \times L}{3600 \times 16.1345 \times S^{0.5}}$	$T_t$shallow	Travel time for shallow concentrated flow (hr)	Numeric (2,3)	≥91.4m	After a maximum of 91.4m, sheet flow usually becomes shallow concentrated flow
M82.4 **G2**	**(Panagos et al., 2012)**	$E = \left(\frac{R}{V}\right) \times S \times \left(\frac{T}{I}\right)$	E	Actual soil loss (t ha^{-1})	Numeric (2,3)	>0,0	
			R	Rainfall-runoff erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1})	Numeric (2,3)	>0,0	Same as M82.2
			V	Vegetation retention factor (dimensionless)	Numeric (2,3)	V≥1	Analogous to the USLE's C-factor • V = 1 for bare, heavily managed agricultural land • V > 1 for land under better management conditions
			S	Soil erodibility factor (t ha h MJ^{-1} ha^{-1} mm^{-1}),	Numeric (2,3)	>0,0	Same as M82.2
			T	Topographic influence (dimensionless)	Numeric (2,3)	>0,0	Corresponding to LS-factor of USLE
			I	Interception of slope length (dimensionless)	Numeric (2,3)		Corresponding to P-factor of USLE

	Variables (1st level)	$V = e^{(LU*F_{cover})}$	LU	Fraction of vegetation (green and brown)	Numeric (2,3)	0-1	Expresses percentage of vegetation in the surface unit (cell) LU value assignment based on linking CORINE LC database and Gavrilovic empirical data (parameter: Xa, (ranging from 0 to 1)
			F_{cover}	Constant corrective parameter	Numeric (2,3)	1-10	Expresses management over the year
		$T = \left(\frac{A_s}{22.13}\right)^{0.4} \times \left(\frac{sin\beta}{0.0896}\right)^{1.3}$	A_s	Flow accumulation (m)	Numeric (2,3)	>0,0	
			β	Slope (rad)	Numeric (2,3)		Slope gradients less than14° (0.25 rad) Slope length up to 100 m Elevation raster cell size less than 30 m
		$I = 1 + \sqrt{\frac{S_f}{255}}$	S_f	Sobel filter value of the satellite image in a range [0,255] (8-bit systems)	Numeric (2,3)		
M82.5 **USPED**	**(Mitasova et al., 1996; Mitas and Mitasova, 1998)**	$T = R \times K \times C \times P \times A^m \times (sinb)^n$	T	Sediment transport capacity rate (per pixel) (t acre^{-1} y^{-1})	Numeric (2,3)	>0,0	SEDIMENT TRANSPORT MODEL
			R				Same as M82.2
			K				Same as M82.2
			C				Same as M82.2

			P				Same as M82.2
			A	Upslope contributing area per unit contour width (m^2 m^{-1})	Numeric (2,3)	>0,0	
			m	Slope length exponent	Numeric (2,3)	1.6 or 1.0	1.6 for prevailing rill erosion 1.0 for prevailing sheet erosion
			b	Slope (degrees)	Numeric (2,3)	>0,0	
			n	Slope steepness exponent	Numeric (2,3)	1.3 or 1.0	1.3 for prevailing rill erosion 1.0 for prevailing sheet erosion
		$K_t \sim K \times C \times P$	K_t	Soil transportability coefficient			Dependent on soil properties and vegetation cover
		$LS \sim A^m \times (sinb)^n$					
		$ED = d(Tcosa)/dx + d(Tsina)/dy$	ED	net erosion/deposition (t acre^{-1} y^{-1})			
			a	Aspect of the terrain surface (degrees)	Numeric (2,3)	>0,0	the direction of maximum hillslope gradient in the horizontal plane in degrees
			dx=dy	Grid resolution			
M82.6 **WATEM/SEDEM**	**(Van Oost et al., 2000; Van Rompaey et al., 2001)**						
	SOIL LOSS COMPONENT	$SL = R \times K \times LS_{2D} \times C \times P$	SL	Soil loss (t ha^{-1} y^{-1})	Numeric (2,3)	>0,0	
			R				Same as M82.2

			K				Same as M82.2
			C				Same as M82.2
			P				Same as M82.2
			LS_{2D}	Two-dimensional slope and slope-length factor (dimensionless)	Numeric (2,3)	>0,0	
	Variables (1st level)	$L_{i,j} = \frac{(A_{i,j} + D^2)^{m+1} - {A_{i,j}}^{m+1}}{D^{m+2} {x_{i,j}}^{m} (22.13)^{m}}$	$L_{i,j}$	Slope length factor for the grid cell with coordinates (i, j)	Numeric (2,3)	>0,0	Unit contributing area replaced the upslope length, i.e., the upslope drainage area per unit of contour length (Desmet and Govers, 1996)
			$A_{i,j}$	Contributing area at the inlet of a grid cell (m^2)	Numeric (2,3)	>0,0	
			D	grid cell side length (m)	Numeric (2,3)	>0,0	
	Variables (2nd level)	$x_{i,j} = sina_{i,j} + cosa_{i,j}$	$a_{i,j}$	Aspect direction for the grid cell (i, j)	Numeric (2,3)	>0,0	
			m	Slope length exponent	Numeric (2,3)	>0,0	
	SEDIMENT ROUTING COMPONENT	$TC = K_{TC} \times E_{PR} = K_{TC} \times R \times K \times (LS_{2D} - 4.1S_{IR})$	TC	Transport capacity (t ha^{-1} y^{-1})	Numeric (2,3)	>0,0	
			K_{TC}	Transport capacity coefficient (m)	Numeric (2,3)	>0,0	Describes the proportionality between the potential for rill erosion and the transport capacity
			E_{PR}	Potential for rill erosion (t ha^{-2} y^{-1})	Numeric (2,3)	>0,0	

	Variables (1st level)	$E_{PR} = E_{PT} - E_{PIR} = R \times K \times LS - aRK_{IR}S_{IR}$	E_{PT}	Potential total erosion (rill + inter-rill) (t ha^{-2} y^{-1})	Numeric (2,3)	>0,0	
			E_{PIR}	Potential inter-rill erosion (t ha^{-2} y^{-1})	Numeric (2,3)	>0,0	
			R				Same as M82.2
			K				Same as M82.2
			a	coefficient			
			K_{IR}	Inter-rill soil erodibility factor (t h MJ^{-1} mm^{-1})	Numeric (2,3)	>0,0	In the case of no data availability is assumed that K_{IR} = K
			LS_{2D}				Same as M82.2
			S_{IR}	Inter-rill slope gradient (m m^{-1})	Numeric (2,3)		
	Variables (2nd level)	$S_{IR} = 6.8 \times {S_g}^{0.8}$	S_g	Slope gradient (m m^{-1})	Numeric (2,3)	>0,0	Govers and Poesen, 1988
M82.7 **Gavrilovic or Erosion Potential Method (EPM)**	**(Gavrilovic, S., 1962, 1970, 1972)**	$W = Th\pi F\sqrt{z^3}$	W	Total annual volume of detached soil (m^3 y^{-1})	Numeric (2,3)	>0,0	
			T	temperature coefficient	Numeric (2,3)	>0,0	
			H	mean annual rainfall (mm)	Numeric (2,3)	>0,0	
			π	number π (3.14)	Numeric (2,3)	>0,0	
			F	catchment area (km^2)	Numeric (2,3)	>0,0	
			z	erosion coefficient	Numeric (2,3)/ Jenks classes	<0.19 0.20-0.40 0.41-0.70	very low low moderate

						0.71-1.00 >1.00	high very high
	Variables (1st level)	$T = \sqrt{\left(\frac{t^o}{10} + 0.1\right)}$	t°	average annual temperature (°C)	Numeric (2,3)	-	
		$z = xy(\varphi + \sqrt{J})$	x	soil protection coefficient	categorical	0.05–0.20 0.05–0.20 0.20–0.40 0.40–0.60 0.60–0.80 0.80–1.00	Mixed and dense forest Thin forest with grove Coniferous forest with little grove, scarce bushes, bushy prairie Damaged forest and bushes, pasture Damaged pasture and cultivated land Areas without vegetal cover
			y	soil erodibility coefficient	categorical	0.20-0.60 0.60-1.00 1.00-1.30 1.30-1.80 1.80-2.00	Hard rock, erosion resistant Rock with moderate erosion resistance Weak rock, schistose, stabilized Sediments, moraines, clay, and other rock with little resistance Fine sediments and soils without erosion resistance
			ϕ	erosion and stream network development coefficient	categorical	0.10-0.20 0.30-0.50	Little erosion on watershed Erosion in waterways on 20–

						0.60-0.70 0.80-0.90 0.90-1.00	50% of the catchment area Erosion in rivers, gullies and alluvial deposits, karstic erosion 50–80% of catchment area affected by surface erosion and landslides Whole watershed affected by erosion
			J	average slope of the watershed (%)	Numeric (2,3)	>0.0 / 100	
	Variables (2nd level)	$G = DR \times W$	G	actual sediment yield (m^3 y^{-1})	Numeric (2,3)	>0,0	
			DR	Retention coefficient	Numeric (2,3)	>0,0	
	Variables (3rd level)	$DR = \frac{(L + L_i)\sqrt{O \times D}}{F(L + 10)}$	O	perimeter of the catchment (km)	Numeric (2,3)	>0,0	
			D	average height distance of the catchment (km)	Numeric (2,3)	>0,0	
			L	length of the principal waterway (km)	Numeric (2,3)	>0,0	
			Li	length of the secondary waterway (km)	Numeric (2,3)	>0,0	
			F	catchment area (km^2)	Numeric (2,3)	>0,0	
	Variables (4th level)	$D = (H_{max} - H_{min}) - H_{min}$	H_{max}	Maximum catchment elevation (m)	Numeric (2,3)	>0,0	
			H_{min}	Minimum catchment elevation (m)	Numeric (2,3)	>0,0	

M82.8 **Koutsoyiannis and Tarla**	**(Koutsoyiannis and Tarla, 1987)**	$G = 15\gamma e^{3P}$	G	Mean annual suspended sediment discharge (t km^{-2})	Numeric (2,3)	>0,0	
			P	mean annual precipitation depth (mm)	Numeric (2,3)	>0,0	
			γ	geological coefficient	Numeric (2,3)	>0,0	
	Variables (1st level)	$\gamma = k_1p_1 + k_2p_2 + k_3p_3$	k_1	Coefficient of low erodibility bedrock	Numeric (2,3)	1.0	alluvial, flysch
			k_2	Coefficient of medium erodibility bedrock	Numeric (2,3)	0.5	marls, sandstones, schists
			k_3	Coefficient of high erodibility bedrock	Numeric (2,3)	0.1	limestones, dolomites, metamorphic, igneous
			p_1	Percentage of low erodibility bedrock appearance in the basin	Numeric (2,3)	0-1	
			p_2	Percentage of medium erodibility bedrock appearance in the basin	Numeric (2,3)	0-1	
			p_3	Percentage of high erodibility bedrock appearance in the basin	Numeric (2,3)	0-1	
M82.9	**ART model (Syvitski et al., 2003)**	$Q_s = a_3A^{a_4}R^{a_5}e^{k_1T}$	Q_s	Long-term sediment load (kg s^{-1})	Numeric (2,3)	>0.0	
			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
			R	Catchment maximum relief (m)	Numeric (2,3)	>0.0	

			T	Mean annual temperature (°C)	Numeric (2,3)		
			a_3	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	6.1×10^{-5}	
			a_4	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	0.55	
			a_5	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	1.12	
			k_1	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	0.07	
		$Q_s = a_6 Q^{a_7} R^{a_8} e^{k_2 T}$	Q_s	Long-term sediment load (kg s^{-1})	Numeric (2,3)	>0.0	
			Q	Mean annual water discharge (m^3 s^{-1})	Numeric (2,3)	>0.0	
			R	Catchment maximum relief (m)	Numeric (2,3)	>0.0	
			T	Mean annual temperature (°C)	Numeric (2,3)		
			a_6	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	1.1×10^{-3}	
			a_7	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	0.53	
			a_8	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	1.1	
			k_2	correlation coefficient (for Lat. > 30°)	Numeric (2,3)	0.06	
	Variables (1st level)	$R = H_{max} - H_{min}$	H_{max}	Maximum catchment elevation (m)	Numeric (2,3)	>0.0	

			H_{min}	Minimum catchment elevation (m)	Numeric (2,3)	>0.0	
M82.10 **BQART model**	**(Syvitski and Milliman, 2007)**	$Q_s = wBQ^{0.31}A^{0.5}RT$ ***for T≥ 2°C*** $Q_s = 2wBQ^{0.31}A^{0.5}R$ ***for T< 2°C***	Q_s	Long-term sediment load (kg s^{-1})	Numeric (2,3)	>0.0	
			w	Correlation coefficient	Numeric (2,3)	0.02 0.0006	for units of kg s^{-1} for units of MT y^{-1}
			B	Accounts for important geological and human factors			
			Q	Mean annual water discharge (m^3 s^{-1})	Numeric (2,3)	>0.0	
			A	Drainage area (km^2)	Numeric (2,3)	>0.0	
			R	Catchment maximum relief (km)	Numeric (2,3)	>0.0	
			T	Basin-averaged temperature (°C)	Numeric (2,3)	≥ 2°C	
	Variables (1st level)	$B = IL(1 - T_E)E_h$	I	Glacier erosion factor	Numeric (2,3)	>0.0	
			L	Basin-averaged lithology factor	Numeric (2,3)	0.5 0.75 1.00 1.50	for basins comprised principally of hard, acid plutonic and/or high-grade metamorphic rocks for basins of mixed, mostly hard lithology, sometimes including shield material for basins of volcanic, mostly basaltic rocks, or carbonate outcrops,

						2.00 3.00	or mixture of hard and soft lithology for basins with a predominance of softer lithologies, but a significant area of harder lithologies for fluvial systems draining a significant proportion of sedimentary rocks, unconsolidated sedimentary cover, or alluvial deposits for basins with an abundance of exceptionally weak material (crushed rock, loess deposits).
			T_E	Trapping efficiency of lakes and man-made reservoirs	Numeric (2,3)	$1 - T_E \leq 1$	
			E_h	Human-influenced soil erosion factor	Numeric (2,3)	0.3 1.00 2.00	for basins with a high-density population PD >200 km^2, and GNP/capita >$15K y^{-1} for basins with a low human footprint (PD < 50 km^2) or those containing a mixture of the competing influences of soil erosion and conservation for basins where the population is high

							(PD > 200 km^2), but GNP/capita is low (≤$2.5K y^{-1}), and where basins have not received the resources to engineer solutions to problems of soil erosion
	Variables (2nd level)	$I = 1 + 0.09A_g$	A_g	Area of the drainage basin as a percent of the total drainage area (%)	Numeric (2,3)	>0.0 / 1.00	
		$Y_s = wBQ^{0.31}A^{-0.5}RT$	Y_s	Mean annual sediment yield (t km^{-2} y^{-1})	Numeric (2,3)	>0.0	
			w	*Same as above*			
			B	*Same as above*			
			Q	*Same as above*			
			A	*Same as above*			
			R	*Same as above*			
			T	*Same as above*			
M83.1 **Dendy and Bolton**	**(Dendy and Bolton, 1976)**	$SY = 674A^{-0.16}$	SY	Mean annual sediment yield (t km^{-2} y^{-1})	Numeric (2,3)	>0.0	
			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
M83.2 **Avendano Salas et al.**	**(Avendano Salas et al., 1997)**	$SY = 4139A^{-0.43}$	SY	Mean annual sediment yield (t km^{-2} y^{-1})	Numeric (2,3)	>0.0	
			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
M83.3	**(Lu et al., 2003)**	$SY = 849.15A^{-0.0785}$	SY	Mean annual sediment yield (t km^{-2} y^{-1})	Numeric (2,3)	>0.0	

Lu et al.			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
M83.4 **Webb and Griffiths**	**(Webb and Griffiths, 2001)**	$Q_s = 193A^{1.04}$	Q_s	Mean annual sediment discharge (t y^{-1})	Numeric (2,3)	>0.0	
			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
M83.5 **Mulder and Syvitski**	**(Mulder and Syvitski, 1996)**	$log(Q_s) = 0.406log(A) + 1.279log(H_{max}) - 3.679$	Q_s	Mean annual sediment discharge (t y^{-1})	Numeric (2,3)	>0.0	
			A	Catchment area (km^2)	Numeric (2,3)	>0.0	
			H_{max}	Maximum catchment elevation (m)	Numeric (2,3)	>0.0	
M83.6 **Geomorphological equation**	**(Lykoudi & Zarris 2004: Zarris, Lykoudi, Panagoulia, 2007)**	$SY = 40.23HI^{1.06}RB^{1.40}K^{0.59}$	SY	Mean annual sediment yield (t km^{-2} y^{-1})	Numeric (2,3)	>0.0	
			HI	Hypsometric Integral (%)	Numeric (2,3)	0-1	
			RB	Bifurcation Ratio of the stream network (net number)	Numeric (2,3)	>0.0	Typical values between 2-4
			K	USLE's soil erodibility factor (t ha Mj^{-1} mm^{-1})	Numeric (2,3)	>0.0	
		$Q_s = {Lb_{max}}^{0.76}DD^{-3.6}$	Q_s	Mean annual sediment discharge (t y^{-1})	Numeric (2,3)	>0.0	
			Lb_{max}	Catchment length (km)	Numeric (2,3)	>0.0	
			DD	Drainage Density of the stream network (km^{-1})	Numeric (2,3)	>0.0	
	Variables (1st level)	$RB = \frac{N_u}{N_{u+1}}$	N_u	Number of streams with order U	Numeric (4)	>0	
			N_{u+1}	Number of streams with order U+1	Numeric (4)	>0	

M84.1 **Revised Morgan-Morgan-Finney model**	**(Morgan et al., 1984; Morgan, 2001, 2005)** WATER PHASE; RAINFALL ENERGY	$ER = R \times A$	ER	Effective rainfall (mm)	Numeric (2,3)	>0.0	
			R	Mean annual rainfall (mm)	Numeric (2,3)	>0.0	
			A	Rainfall interception coefficient (%)	Numeric (2,3)	0-1	
		$LD = ER \times CC$	LD	leaf drainage	Numeric (2,3)	>0.0	
			CC	percentage canopy cover (%)	Numeric (2,3)	0-1	
		$DT = ER - LD$	DT	direct throughfall	Numeric (2,3)	>0.0	
		$KE = KE(DT) + KE(LD)$	KE	total kinetic energy of the ER (J m^{-2})	Numeric (2,3)	>0.0	
			KE(DT)	kinetic energy of direct throughfall (J m^{-2})	Numeric (2,3)	>0.0	
			KE(LD)	kinetic energy of leaf drainage (J m^{-2})	Numeric (2,3)	>0.0	
	Variables (1nd level)	$KE(DT) = DT \times KE$	KE	kinetic energy of precipitation (J m-2 mm^{-1})	Numeric (2,3)	>0.0	
		$KE(LD) = 15.8PH^{0.5}$	PH	height from which raindrops fall from the vegetation cover to the ground surface (m)	Numeric (2,3)	>0.0	if KE(LD)<0 then KE(LD) is set to 0
	Variables (2rd level)	$KE = 9.81 + 11.25log_{10}I$	I	rainfall intensity (mm h^{-1})	Numeric (2,3)/ Jenks classes	10 25 30 >0.0	temperate climates (no data) tropical climates (no data) climates with intense seasonal variations like Mediterranean

					Numeric (2,3)		type/monsoon (no data) when data are available
	WATER PHASE; RUNOFF	$Q = R \times exp\left(-\frac{R_c}{R_o}\right)$	Q	annual runoff (mm)	Numeric (2,3)	>0.0	
			R_o	mean rain per erosive rain day (mm)	Numeric (2,3)	>0.0	
			R_c	moisture storage capacity of the soil (mm)	Numeric (2,3)	>0.0	
			R	mean annual rainfall (mm)	Numeric (2,3)	>0.0	
	Variables (1st level)	$R_o = \frac{R}{R_n}$	R_n	number of rain days per year (rain days)	Numeric (2,3)	>0.0	
		$R_c = 1000 \times MS \times BD \times EHD \times {}^{E_t}/_{E_o}$	MS	Moisture content of the soil at field capacity or 1/3 bar tension (% w w^{-1})	Numeric (2,3)	0-1	
			BD	bulk density of the topsoil layer (Mg m^{-3})	Numeric (2,3)	>0.0	
			EHD	effective hydrological depth of the soil (m)	Numeric (2,3)	>0.0	
			E_t	actual evapotranspiration	Numeric (2,3)	>0.0	
			E_o	potential evapotranspiration	Numeric (2,3)	>0.0	
	SEDIMENT PHASE; PARTICLE DETACHMENT BY RAINDROP IMPACT	$F = K \times KE \times 10^{-3}$	F	Soil particle detachment by raindrop impact (kg m^{-2})	Numeric (2,3)	>0.0	

			KE	total kinetic energy of the ER (J m^{-2})	Numeric (2,3)	>0.0	
			K	soil detachability index (g j^{-1})	Numeric (2,3)	>0.0	
	SEDIMENT PHASE; PARTICLE DETACHMENT BY RUNOFF	$H = Z \times Q^{1.5} \times sinS \times (1 - GC) \times 10^{-3}$	H	soil particle detachment by runoff (kg m^{-2})	Numeric (2,3)	>0.0	
			Z	resistance of soil to erosion	Numeric (2,3)	>0.0	
			Q	runoff (mm)	Numeric (2,3)	>0.0	
			S	slope steepness (º)	Numeric (2,3)	0-90	
			GC	ground cover (%)	Numeric (2,3)	0-1	
	Variables (1nd level)	$Z = \frac{1}{0.5COH}$	COH	soi cohesion (kPa)	Numeric (2,3)	>0.0	
	SEDIMENT PHASE; TRANSPORT CAPACITY OF RUNOFF	$TC = C \times Q^2 \times sinS \times 10^{-3}$	TC	transport capacity of runoff (kg m^{-2})	Numeric (2,3)	>0.0	
			C	crop management factor			
			S	slope steepness (º)	Numeric (2,3)	>0.0	
	EROSION	$D = F + H$	D	total annual detachment rate of soil (kg m^{-2})	Numeric (2,3)	>0.0	
			F	Soil particle detachment by raindrop impact (kg m^{-2})	Numeric (2,3)	>0.0	
			H	soil particle detachment by runoff (kg m^{-2})	Numeric (2,3)	>0.0	

	GROSS EROSION	$GE = min(D \times 10, TC \times 10)$	GE	annual erosion rate or gross erosion (t ha^{-1} y^{-1})	Numeric (2,3)	>0.0	
M84.2 **Hydraulics [sediment discharge rating curves, runoff (Q) - sediment discharge (Qs) curves]**	**(Koutsoyiannis,2000 & Zarris, Lykoudi, Koutsoyiannis 2002)**	$Q_{is}= aQ_i^{b} n_i$	Q_s Q a,b η	Mean annual sediment discharge (M^3/T, m^3/s) River discharge (M^3/T, m^3/s), Sediment rating coefficient and exponent correspondingly is the multiplicative error term which exhibits a lognormal distribution	Numeric (2,3)	>0.0	

2.19.4 Assessment of soil erosion models and tools

A summary assessment of soil erosion models and tools that have been presented in chapters 2.17-2.19 is given in appendix 5.12 (Table 64-Table 67).

2.20 M85: Soil quality indices

2.20.1 Introduction

Soil quality is *"the capacity of a soil to function, within the ecosystem and land-use boundaries, to sustain biological productivity, maintain environmental quality, and promote plant and animal health"* (Doran & Parkin, 1994). To determine the soil quality, the physical, chemical and biological characteristics of the soil are taken into account, either individually or in combination. Because soil consists of solid, liquid and gas phases, the assessment of soil quality becomes a complex process. Factors such as parent material, topography, climate and hydrology may affect potential values of various soil properties in such a way that it is not possible to establish universal target values. Baseline or reference values must therefore be included in the assessment of soil quality (Bünemann et al., 2018).

Soil quality is mainly assessed using the physical and chemical characteristics of the soil. The main physical parameters used in this evaluation are the soil particle size distribution, the bulk density, the available water, etc and the main chemical parameters are the organic carbon content of the soil, the pH, the total N, heavy metals etc. Recently, new studies showed that soil organisms play an important role in soil functioning, and thus the inclusion of biological and biochemical indicators may contribute to a better assessment of soil quality. Several techniques for determining soil microbial characteristics, such as microbial biomass and respiration (e.g., chloroform fumigation extraction, substrate-induced respiration, 1-day CO_2 test) are reported in the literature (Muñoz-Rojas, 2018).

The most common indices, according to the literature, to assess soil quality and pollution are explained below and presented in Table 39. Most of them are simple equations that are relatively easy to compute.

2.20.2 Relevant models

2.20.2.1 Overview and description of relevant models

Many calculation methods exist for the evaluation of environmental quality. It is very important to choose the appropriate method of assessing soil quality for decision-making and selection of sustainable management practices.

Various pollution indices are used to assess the degree of pollution in the soil and can to some extent help to predict the future sustainability of the ecosystem (Kowalska et al., 2018). The calculation of many of these indices requires an assessment of the geochemical background (GB) in order to distinguish between natural concentrations of the various elements in the soil and those of anthropogenic origin.

The most used pollution indices according to Doležalová Weissmannová and Pavlovský (2017) are divided into a) the single indices and b) the total composite indices which include integrated indices and ecological risk indices. The simple indices for their calculation take into account each individual metal in the soil and are used to classify the soils into different categories according to their degree of pollution (Geoaccumulation Index (I_{geo}), Enrichment Factor (EF), Pollution Index (PI), and Contamination Factor (C_f)). The total composite indices use more than one metal, and their calculation is based on the simple indices (Pollution Load Index (PLI), Nemerow Pollution Index ($PI_{Nemerow}$), Degree of Contamination (C_{deg}), Modified Contamination Factor (mC_{deg})).

The most common indices are described in the following:

M85.1 This Soil Quality Index **(SQI)** (Amacher et al., 2007) incorporates 19 physical and chemical soil properties that have been identified by expressing them as a single number and it could be an indicator of overall **forest soil quality**. It has the potential to be used as a tool for monitoring changes in the physicochemical parameters of forest soils over time and under certain conditions as a risk indicator of forest decline. The SQI can also be used as an indicator of the potential for soil quality change due to the action of various environmental stressors (for example, atmospheric deposition, changes in global cycles, and so forth).

M85.2 Geoaccumulation Index **(Igeo)** allows the assessment of heavy metal contamination of soil based on its content in the A or O horizons taking into account specific GB (Müller, 1969). It is widely used and helps to compare current and past contamination (Kowalska et al., 2018); (Müller, 1969).

M85.3 The Single Pollution Index **(PI)** (Al-Anbari et al., 2015) can be used to evaluate the pollution degree of the soil and to determine which heavy metal represents the highest threat for a soil environment. It is also used for the calculations of some of complex indices. It is widely used and very easy to apply.

M85.4 The Enrichment Factor **(EF)** (Abrahim & Parker, 2008) expresses the potential impact of anthropogenic activity on heavy metal concentrations in soil. It is also useful for determining the origin of heavy metals. Reference elements are often introduced for standardization to calculate the EF.

M85.5 The Contamination Factor **C_f** (Inengite et al., 2015) is used for the assessment of soil contamination and for the evaluation of soil quality. It also helps to describe toxic substances.

M85.6 The Biogeochemical Index **(BGI)** (Mazurek et al., 2017) is a current indicator that helps to assess the degree of heavy metal concentration in the O horizon under forest and grassland vegetation and can demonstrate vertical mobility of heavy metals. Knowledge of heavy metal concentrations in both the O and A horizons is required to calculate the index.

M85.7 The Pollution Load Index **(PLI)** (Varol, 2011) is useful for the overall assessment of the degree of soil and sediment contamination. This indicator shows the deterioration of soil conditions due to the accumulation of heavy metals.

M85.8 The Multi-element contamination **(MEC)** (Adamu & Nganje, 2010) makes a comprehensive assessment, taking into account all heavy metals identified. It is easy to apply and can provide information on the origin of heavy metals.

M85.9 The Contamination security index **(CSI)** (Pejman et al., 2015) is used for the assessment of the intensity of heavy metal accumulation. It helps to determine the toxicity limit above which adverse effects on soil are observed.

M85.10 The Nemerow Index **($PI_{Nemerow}$)** is used to estimate the overall degree of soil pollution as well as soil quality. It is a widely used indicator that incorporates all individual heavy metals. It applies to both O and A horizons (Qingjie et al., 2008)**;** (Kowalska et al., 2018).

M85.11 The Degree of Contamination **(C_{deg})** is a complex index used as an evaluation tool of soil and sediment contamination (Hakanson, 1980).

M85.12 The Modified Contamination Factor **(mC_{deg})** helps to better assess the overall pollution of soils and sediments by heavy metals (Abrahim & Parker, 2008); (Mazurek et al., 2017).

Table 39 provides an overview of soil quality indices, along with their main variables.

Table 39: Soil quality indices.

Model Name	Model/Indices	Mathematical expression	Variable	Description	Type	Range	Verbal
M85.1	Soil Quality Index (SQI) (Amacher et al., 2007)	Total SQI=individual soil property index values	SQI	Soil Quality Index	Numeric		Higher index scores represent better soil quality
M85.2	Geoaccumulation Index (Igeo) (Müller, 1969); (Kowalska et al., 2018)	$I_{geo} = \log_2\left(\frac{C_n}{1.5GB}\right)$	I_{geo}	Geoaccumulation Index	Numeric	Igeo ≤ 0 0 ≤ Igeo < 1 1 ≤ Igeo < 2 2 ≤ Igeo < 3 3 ≤ Igeo < 4 4 ≤ Igeo < 5 Igeo > 5	Unpolluted Unpolluted to moderately polluted Moderately polluted Moderately to strongly polluted Strongly polluted Strongly to extremely polluted Extremely high polluted
			C_n	Concentration of individual heavy metal			
			GB	Value of geochemical background			
M85.3	Single Pollution Index (PI) (Al-Anbari et al., 2015)	$PI = \frac{C_n}{GB}$	PI	Single Pollution Index	Numeric	PI < 1 1 < PI ≤ 3 3 ≤ PI	Unpolluted, Low level of pollution Moderate polluted Strong polluted
			C_n	the content of heavy metal in soil	Numeric	>0	
			GB	values of the geochemical background	Numeric	>0	
M85.4	Enrichment factor (EF) (Abrahim & Parker, 2008)	$EF = \frac{\left[\frac{C}{LV}\right] sample}{\left[\frac{GB}{LV}\right] background}$	EF	Enrichment factor	Numeric	EF < 2 EF = 2–5 EF = 5–20 EF = 20–40 EF > 40	Deficiency to minimal enrichment Moderate enrichment Significant enrichment Very high enrichment Extremely high enrichment
			$\frac{C_n}{LV} sample$	content of analyzed heavy metal (Cn) and one of the following metals Fe/Al/Ca/Ti/Sc/Mn (LV) in the sample	Numeric	>0	

			$\frac{GB}{LV} backgrou$	reference content of the analyzed heavy metal (Cn) and one of the following metals Fe/Al/Ca/Ti/Sc/ Mn (LV)	Numeric	>0	
M85.5	Contamination factor (C_f) (Inengite et al., 2015)	$Cf = \frac{C_m}{C_{p-i}}$	C_f	Contamination factor	Numeric	Cf < 1 1 < Cf ≤ 3 3 ≤ Cf ≤ 6 6 ≤ Cf	Low contamination factor Moderately contaminated factor Considerably contaminated factor Very high contaminated factor
			C_m	mean content of heavy metal from at least five samples of individual metals	Numeric	>0	
			C_{p-i}	preindustrial reference value for the substances	Numeric	>0	
M85.6	Biogeochemical Index (BGI) (Mazurek et al., 2017)	$BGI = \frac{C_nO}{C_nA}$	BGI	Biogeochemical Index	Numeric	>1	increased ability of heavy metal sorption by the O horizons of soil.
			C_nO	content of a heavy metal in the O horizon	Numeric	>0	
			C_nA	content of a heavy metal in the A horizon	Numeric	>0	
M85.7	Pollution Load Index (PLI) (Varol, 2011)	$PLI = \sqrt[n]{PI_nPI_2 \dots PI_n}$	PLI	Pollution Load Index	Numeric	PLI > 1 PLI = 1 PLI < 1	Polluted Baseline levels of pollution Not polluted
			PI	calculated values for the Single Pollution Index	Numeric	>0	
			n	the number of analyzed heavy metals	Numeric	>0	
M85.8	Multi-element contamination		**MEC**	Multi-element contamination	Numeric	MEC>1	anthropogenic impact on

	(MEC) (Adamu & Nganje, 2010)	$MEC = \frac{\left(\frac{C_1}{T_1}+..+\frac{C_n}{Tn}\right)}{n}$					heavy metal concentration
			C	content of heavy metal	Numeric	>0	
			T	tolerable levels given by Kloke (1979)	Numeric	>0	
			n	the number of heavy metals	Numeric	>0	
M85.9	Contamination security index (CSI) (Pejman et al., 2015)	$CSI = \sum_{i=1}^{n} W\left(\left(\frac{C}{ERL}\right)^{\frac{1}{2}} + \left(\frac{C}{ERM}\right)^{2}\right)$	**CSI**	Contamination security index	Numeric	<0.5 0.5-1 1-1.5 1.5-2 2-2.5 2.5-3 3-4 4-5 >5	uncontaminated very low severity low severity low to moderate severity moderate severity moderate to high severity high severity very high severity ultra-high severity
			w	computed weight of each heavy metal (Pejman et al. 2015)	Numeric	>0	
			C	concentration of heavy metal	Numeric	>0	
			ERL	values given by Long et al. (1995)	Numeric	>0	
			ERM	values given by Long et al. (1995)	Numeric	>0	
			n	number of investigated toxic elements	Numeric	>0	
M85.10	Nemerow pollution index (Qingjie et al., 2008); (Kowalska et al., 2018)	$PI_{Nemerow=}\sqrt{\frac{\left(\frac{1}{n}\sum_{i=1}^{n} PI\right)^{2} + PI_{max}^{2}}{n}}$	$PI_{Nemerow}$	Nemerow pollution index	Numeric	<0.7 $0.7 \le PI_{Nemerow} <$ 1.0 $1.0 \le PI_{Nemerow} <$ 2.0 $2.0 \le PI_{Nemerow} <$ 3.0 $PI_{Nemerow}$ >3.0	safety domain precaution domain slightly polluted domain moderately polluted domain seriously polluted domain

			PI	calculated values for the Single Pollution Index				
			PI_{imax}	maximum value for the Single Pollution				
				Index of all heavy metals				
			n	number of heavy metals				
M85.11	Degree of contamination (Hakanson, 1980)		C_{deg}	Degree of contamination	Numeric	Cdeg < 8 8 ≤ Cdeg ≤ 16 16 ≤ Cdeg ≤ 32 32 ≤ Cdeg	Low degree of contamination Moderate degree of contamination Considerable degree of contamination Very high degree of contamination	
			CF	contamination factor of single heavy metal				
			n	number of heavy metals				
M85.12	Modified Contamination Factor (Abrahim & Parker, 2008); (Mazurek et al., 2017)	$mC_d = \frac{\sum^{C} F}{\pi}$	mC_{deg}		Numeric	mC_d < 1.5 1.5 ≤ mC_d < 2 2 ≤ mC_d < 4 A 4 ≤ mC_d < 8 A 8 ≤ mC_d < 16 A 16 ≤ mC_d < 32	nil to a very low degree of contamination low degree of contamination moderate degree of contamination high degree of contamination very high degree of contamination	

2.20.2.2 Assessment of relevant models

A summary assessment of soil quality indices is provided in appendix 5.13 (Table 68).

2.21 M86: Desertification indices

2.21.1 Introduction

According to the “Special Report: Combating desertification in the EU: a growing threat in need of more action (europa.eu)” (https://op.europa.eu/webpub/eca/special-reports/desertification-33-2018/en/), the risk of desertification in the EU was not being effectively and efficiently addressed. While desertification and land degradation are growing threats, the steps taken to combat desertification lack coherence. There is no shared vision in the EU about how land degradation neutrality will be achieved by 2030.

Following the definition of United Nations Convention to Combat Desertification (UNCCD, 1994), desertification is defined as land degradation in arid, semi-arid, and dry sub-humid areas resulting from many factors, including climatic variations and human activities. Desertification is measured/estimated based on the Ariditiy Index (AI) which is the ratio of average annual precipitation amount (P) to potential evapotranspiration amount (PET). Nevertheless, AI is not considered to be an accurate proxy for desertification in increasing CO2 environments. Considering the fact that earth is currently an increasing CO2 environment, Ai is not the best measure. Moreover, other metrics can be used such as precipitation, soil moisture, but again these do not provide clear indications that dryland extents will change over time, especially on a climate change/crisis environment (Mirzabaev et al., 2019).

Environmental (e.g., climate regime, rainfalls, droughts, topography) and anthropogenic (e.g., agricultural intensification, deforestation, water resources misuse) factors contribute to land degradation (Salvia et al, 2019).

Desertification is directly addressed by UN Sustainability Goal No 15: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.

2.21.2 Relevant models

2.21.2.1Overview of relevant models

Table 40 provides an overview of existing desertification indices.

Table 40: Desertification indices.

Model Code	**Method/ Model Name**	**Model Nature**	**SILVANUS Phase**	**Main capabilities in keywords**	**Main Limitations**
M86.1	Kosmas et al., 1999 (ESA & RDI)	Empirical	Phase A & Phase C	Desertification, soil, vegetation, climate, land use. Methodology for mapping Environmentally Sensitive Areas (ESAs) to desertification. Indicators for desertification at European/National and Regional scales. Targeted for Europe. Used by the European Environment Agency (https://www.eea.europa.eu/data-and-maps/figures/sensitivity-to-desertification-index-map)	
M86.2	Santili et al., 2010	Empirical/Mathematical	Phase A & Phase C	Desertification index, IDI, GIS. Tested and applied in Italy. Can be applied in other areas as well.	
M86.3	Chen et al., 2021	Mathematical	Phase A & Phase C	Remote sensing-based desertification index (RSDI), Spatial distribution, Trend analysis, Driving forces, Restoration	Application in China (sand-belt zones)
M86.4	Dharumarajan et al., 2017	Mathematical	Phase A & Phase C	Desertification, desertification vulnerability indices, prediction, random forest model, variable importance	
M86.5	Wu et al., 2019	Mathematical	Phase A & Phase C	Albedo, MSAVI, Feature space,	

	(SASDI model)			Desertification index, Remote sensing monitoring. Landsat images as input. Semi-arid grassland degradation.	
M86.6	Kempf, 2021	Mathematical	Phase A & Phase C	NDVI, desertification, landcover	Tested in Northern China and Mongolia. Uses NDVI from MODIS images.. Copernicus Preprint. Revision not accepted (https://cp.copernicus.org/preprints/cp-2021-5/)
M86.7	Dragan et al., 2005	Mathematical	Phase A & Phase C	climatology, NDVI, GIS, deserts, Lebanon	Study area: only in Lebanon
M86.8	Tuama et al., 2020	Mathematical	Phase A & Phase C	NDVI, SPC, Landsat OLI8	Study area: only in China.
M86.9	Brandt and Geeson, 2015	Empirical/Mathematical	Phase A & Phase C	Tested in Europe. Most probably it is based on ESA index (Kosmas et al., 1999).	
M86.10	Xu et al., 2022	Mathematical	Phase A & Phase C	UAV, desertification, grassland. Vegetation coverage examined.	Study area: grasslands in China
M86.11	Khanamani, et al., 2022	Empirical/Mathematical	Phase A & Phase C	MEDALUS, GIS, Desertification, Soil, Isfahan. Based on the MEDALUS model (Kosmas et al., 1999)	
M86.12	dos Santos et al., 2022	Empirical/Mathematical	Phase A & Phase C	Land degradation, Spatial modeling, Geoprocessing, Climate. Aridity index Ia (P/PET) and D (PET/P)	Study area: only in Brazil
M86.13	Guishan et al., 2011	Empirical/Mathematical	Phase A & Phase C	Desertification, LANDSAT, Tm monitoring, NDVI, MSAVI, remote sensing. Vegetation and soil change indices extracted from seven LANDSAT TM images. Two methods were applied. A: the desertification extent and tendency were determined by classifying the land cover into the following four categories using the Normalized Difference Vegetation Index (NDVI): floating desert area, half-fixed sand area, fixed sand area, and grassland. B: the degree of desertification was classified using the Modified Soil Adjusted Vegetation Index (MSAVI): primitive state, latent state, slight desertification, medium desertification, and high-degree desertification.	Study area only in China
M86.14	Perez-Marin et al., 2022	Empirical/Mathematical	Phase A & Phase C	land degradation; environmental monitoring; soil organic carbon; multiple soil classes; adaptation. 24 which reduced to 11 soil indicators tested.	Study area in Brazil. 11 soil indicators used which makes it hard to implement.

2.21.2.2 *Description of relevant models*

The models that calculate or estimate desertification mostly focus on parameters such as the soil, climate, vegetation and human intervention. Methods can be based on in situ data, but the recent years satellite and aerial (UAV) images are used to estimate desertification in various areas worldwide. Among the various indexes used, Aridity Index (AI) and NDVI are commonly used to estimate desertification. GIS are mainly used as the tools capable to analyse, visualise and finally assess and estimate desertification.

MEDALUS method (Kosmas et al., 1999): Among the most commonly used methods, also used the European Environmental Agency is the MEDALUS method. This method considers soil quality, meaning, the parent material, the fragmentation of rocks, the soil depth, the capability of soil to absorb water, the slope gradient, the soil structure stability and salinization. Another critical factor is the quality of climate (e.g., arid, semi-arid), and consequently precipitation, aridity and aspect. Moreover, the type of vegetation also plays a significant role as it is strongly connected to wildfires and the ability of plants to recover, soil erosion, drought resistance and plant cover. Finally, humans contribute to desertification according to the use of land, the intensity of the use, the overgrazing, the abandonment of lands, and the fires caused either by negligence or arson. This method has also been used by Khanamani et al., (2022) in Isfahan (Iran) and Brandt and Geeson (2015).

The main advantage of this method is that it has been tested in the Mediterranean and South Europe and now is used as the main index for desertification in Europe through the concept of Environmentally Sensitive Areas (ESAs).

Santini et al. (2010) proposed the Integrated Desertification Index (IDI) to combine in a semi-quantitative way multiple processes leading to desertification and simulated via mechanistic to empirical models. The outcomes from the modelling efforts on different desertification components are standardized and weighted so to be inserted in the IDI formulation. The peculiarity of IDI is that it also takes into account the temporal dimension of land degradation and desertification phenomena by integrating the standardized value of current hazards, simulated for the single desertification components, and their variation from the past, so to consider that some processes can have different either magnitude or rapidity.

Chen et al., 2021 propose a Remote Sensing-Based Desertification Index (RSDI) considering modified soil adjusted vegetation index (MSAVI), the topsoil grain size index (TGSI), Wetness and Albedo. By combining these four indices and calculating trends for a set of data of 10 years. The study areas were in Northern China. Similarly, Wu et al., 2019 propose the SASDI model, again based on remoting sensing data for semi-arid grasslands. Dragan et al., (2015) studied desertification in Lebanon based on the NDVI index. Tuama et al., (2020) use NDVI with the use of other indices as well to study desertification in China. Xu et al., (2022) use UAVs to study a series of vegetation indices. A similar approach from remote sensing is followed by Guishan et al., (2011). In Brazil, dos Santos et al., (2022) used the aridity index to examine desertification susceptibility. Again, in Brazil, Perez-Marin et al., (2022) used biophysical factors of soil (chemical and physical) and woody coverage of the area to study desertification.

2.21.2.3 Assessment of relevant models

The use of in situ data varying from soil to geology, climate, vegetation and human activity either in a qualitative or quantitative way provide in general good estimates. The use of new technologies exploiting remote sensing provide easiness to monitor large areas in a faster manner. Methods that have been tested in Europe can be considered as more valid or calibrated in the reality of Europe. This does not necessarily mean that methods that have been used in other areas are not good. Also, the use of various indices, such as the NDVI, the aridity index or combinations of indices, that can be found from satellite images may be easier to be implemented by platforms such as SILVANUS, compared to other methods that require in situ measurements, unless these data can be found and fed into the SILVANUS platform.

2.21.3 Relevant tools

2.21.3.1 Overview of relevant tools

Table 41 provides an overview of existing tools that make use of desertification indices.

Table 41: Overview of tools that use desertification indices.

Tool Code	Name	Environment	Phase	Main capabilities in keywords	Main Limitations
T86.1	Integrated Desertification Index (IDI)	GIS	Phase A & Phase C	Desertification, index, GIS. Application of the Santini et al., 2010 method	
T86.2	ESA index (MEDALUS method)		Phase A & Phase C	The MEDALUS method	No tool available
T86.3	DIS4ME	Web browser	Phase A & Phase C	Web access tool for understanding the MEDALUS method; Indicators listed	No tool that makes calculations
T86.4	Environmental Sensitivity Index - ESI index (DIS4ME project)	Web-browser (online tool)	Phase A & Phase C	Estimation of desertification. Easy to use (https://esdac.jrc.ec.europa.eu/public_path/shared_folder/projects/DIS4ME/esi_jan_05/esi.htm#tool)	Scale: application within a land unit

2.21.3.2 Assessment of relevant tools

The use of GIS systems in desertification studies is extremely important, as they provide the necessary tools to assess data with spatial extent. The MEDALUS method is provided in the DIS4ME project website, but only the theoretical background. ESI (T86.4) can be used online through a respective tool, but with the disadvantage of point locations and on a manual basis inserted by the user.

3. Conclusions

Chapter 2 provided a comprehensive overview and analysis of existing forest models and tools that can contribute, directly or indirectly, in environmentally sustainable and resilient forests. Concluding this deliverable, it is important to synthesize the insights gained from the analysis of the various model categories. Table 42 presents a comprehensive overview of the different categories of forest-related models discussed throughout this report. It provides a clear representation of how each model category aligns with different phases in integrated fire management and its applicability within the Wildland-Urban Interface (WUI) areas. In the table, the "Use in Phase" column categorizes the models according to their relevance across the three different phases, namely A) prevention and preparedness; B) detection and response; and C) restoration and adaptation, serving different needs, such as Training, Planning, Forest Resilience, Firefighting, Fire Impact Mitigation, Reforestation, Simulation, Citizens Protection, and Soil Protection. Furthermore, the "Valuable for WUI" column indicates whether a particular model category is specifically beneficial for the unique challenges faced by communities located within the WUI. This is a critical aspect, as WUI areas require tailored strategies to mitigate fire risks and protect both human populations and natural ecosystems.

Table 42: Overview of model categories and their applicability to different Phases and to WUI.

Code	Model Category	Use in Phase			Valuable for WUI
		A	B	C	
M11	Strategies and methodologies for resource deployment and management tactics	— Training — Planning	— Firefighting	-	YES
M21	Fire behavior models	— Training — Planning — Forest resilience	— Firefighting	-	YES
M22	Models for canopy fuel load estimation	— Training — Planning — Forest resilience	— Firefighting	-	YES
M23	Models, methodologies and indices for fire risk assessment and fire damage estimation	— Training — Planning — Forest resilience	— Firefighting	-	YES
M24	Models of surface fuel load	— Training — Planning — Forest resilience	— Firefighting	-	YES
M31	Models for predicting future Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) using Stand Basal Area Increment	— Training — Planning — Forest resilience	— Firefighting	-	YES
M41	Models for climate change impact on forests	— Training — Forest resilience	— Firefighting	— Fire impact mitigation	YES
M42	Models for calculation of local weather conditions	— Training — Forest resilience	— Firefighting	-	YES
M43	Models for estimating the effect of environmental factors on forest susceptibility to fire	— Training — Forest resilience	— Firefighting	-	YES
M51	Models for wildfire ignition prediction	— Training — Forest resilience		— Fire impact mitigation	YES
M61	Enhancement of forest resilience through forest management treatments	— Training — Forest resilience		— Fire impact mitigation	YES

M62	Models of biodiversity index and ecological site classification	— Training — Forest resilience		— Fire impact mitigation — Reforestation	NO
M63	Models for the development of forest and landscape management	— Forest resilience		— Fire impact mitigation — Reforestation	YES
M71	Models for estimating air quality and corresponding risk for human health during forest fires	— Simulation — Training	— Citizens protection	— Mitigation of fire impact to population	YES
M72	Models to simulate and support evacuation needs due to forest fire event	— Training	— Citizens protection	-	YES
M82	Models for soil erosion	— Soil protection		— Mitigation	NO
M83	Geomorphological and topographic models for sediment yield and discharge	— Resilience		— Mitigation	NO
M84	Soil erosion models focused on hydraulics	— Resilience		— Mitigation	NO
M85	Soil quality indices	— Resilience		— Mitigation	NO
M86	Desertification indices	— Resilience		— Mitigation	NO

The following paragraphs provide a summary and concise conclusions from each section (category of models and tools).

M11: Strategies and methodologies for resource deployment and management tactics (chapter 2.2). The provided list includes both mathematical models and tools, all of which pertain to the domain of firefighting, particularly wildland firefighting. Most of the models (M11.1 to M11.48) are mathematical in nature, with some being based on empirical data or GIS. These models cover a wide range of aspects related to firefighting, including safety zones estimation, resource allocation and deployment, fire truck deployment optimization, and dispatching resources. Most models focus on Phase B, though some are applicable to both Phases A and B. Many models involve optimization techniques, with some integrating specific algorithms or methodologies such as greedy algorithms, Monte Carlo simulation, and MILP (Mixed-Integer Linear Programming). Several models also integrate GIS (Geographic Information Systems) for spatial analysis, indicating a significant emphasis on the spatial aspect of firefighting. The tools (T11.1 to T11.11) vary from desktop to mobile applications, with some being platform-specific (e.g., Windows, Linux, iOS, Android). These tools provide functionalities ranging from calculating safety zones, managing and coordinating firefighter activities, GIS mapping, and 3D representation of the Earth. Notably, there's a tool (T11.9 - Google Earth) which is widely recognized outside the domain of firefighting but appears to have applicability within this domain as well. Some tools, such as SSDE (Safe Separation Distance Evaluator), are web-based and integrate with other platforms like the Earth Engine App. Some tools are directly linked to specific mathematical models. For instance, the WiSE tool (T11.1) integrates the Butler and Cohen (1998) model (M11.1), and the SSDE tool (T11.11) integrates the Campbell et al. (2022) model (M11.6). Overall, the emphasis on safety zones and resource allocation, both in terms of mathematical models and tools, indicates the critical importance of these aspects in wildland firefighting. The integration of mathematical models with tools suggests a seamless transition from theoretical frameworks to practical applications, facilitating real-world decision-making for firefighting professionals. The diversity of models and tools, from safety zones to resource deployment and GIS mapping, underscores the multifaceted challenges faced by firefighting professionals and the comprehensive solutions developed to address them.

M21: Fire behavior models (chapter 2.3). The model by Rothermel (1972) is a semi-empirical mathematical model used in phases A and B. It predicts the surface fire rate of spread and is sensitive to wind measurements and accurate fuel descriptions. The models by Byram (1959) and Albini (1976) are mathematical models for predicting Fireline Intensity (FI) and Flame Length (FL) for surface fires in phases A and B. The model by Anderson (1969) is a mathematical model in phases A and B that predicts flame residence time for surface fires. The model by Van Wagner (1977) is an empirical model used in phases A and B for crown fires, estimating critical surface intensity and crown fire rate of spread. The models by Rothermel (1991) and Thomas (1963) are empirical and mathematical models, respectively, used in phases A and B to predict various aspects of crown fires. Albini (1979, 1981, 1983a, 1983b) and Chase (1981, 1984) primarily focus on predicting spotting distances from various fire sources using mathematical models in phases A and B. Morton (1965) and Morris (1987) use mathematical models in phases A and B to model fire plumes and wind-driven spotting fires, respectively. Canadian Forest Fire Behavior Prediction System is an empirical model providing extensive fire behavior estimates and predictions across various phases. The models by Bogdos and Manolakos (2013) and Coen et al. (2013) are mathematical models in phases A and B that focus on surface fire behaviors influenced by different factors. The model by Linn, R. (1997) and the CFD model delve into the dynamics of surface fires, capturing fluid mechanics, heat transfer, and wildland fire propagation. On the software side, Wildfire Analyst and WFA Pocket are SW-GIS style tools providing real-time wildfire behavior modeling, spread, and risk analysis. BehavePlus, Nexus 2.1, FlamMap 6.0, and FARSITE 4.0 are PC-based tools that predict various fire behavior attributes, integrating several established fire spread models. PyTorch uses machine learning to detect fire spread using aerial imagery, while WRF-Fire offers real-time fire spread modeling based on current weather conditions. Prometheus and Burn P3 focus on fire growth simulation and burn probability computations, respectively. FireFamily+ provides information on fuel moisture and fire danger based on the US National Fire Danger Rating System. FOFEM, FEIS, ArcFuels, and WFAS are tools offering varied functionalities, from fire effects modeling to fire spread prediction, integrated with multiple data sources and models. HIGRAD/FIRETEC is a physics-based tool for simulating the relationship between fire and its environment. FireStation, FIREMAP, QGIS Fire Mapping Tool, Fsim, WFDSS, and FROST Family are tools ranging from numerical fire spread simulations to fire risk assessments and mapping tools, each catering to specific needs in fire management.

M23: Models for canopy fuel load estimation (chapter 2.4). The estimation of the available canopy dry weight is traditionally achieved through a labor-intensive process involving destructive sampling of trees and subsequent oven-drying. To streamline this, allometric models have been introduced for various species, particularly in South Europe and North America. These models primarily rely on Ordinary Least Squares (OLS) theory, with the power model being a favored nonlinear form. To ensure the model's reliability, log-log transformations and a correction factor are applied. Some research has also utilized weighted nonlinear regression as an alternative approach. The primary predictor for these models is the Diameter at Breast Height (DBH), which is readily available in forest inventories. Additional potential predictors include total tree height, crown width, length of the live crown, and tree age. However, the introduction of too many variables can complicate the model, especially when data on certain variables are lacking. Two primary methods are used to estimate canopy fuel load at the stand level. The traditional method involves allometric relationships based on individual tree data. The advanced method predicts the stand-level canopy fuel load directly from stand parameters. This method uses parameters like the number of stems per hectare, Basal Area, Reineke's Stand Density Index, dominant height, and the Relative Spacing Index. The advanced method is favored for its direct approach and use of primary variables, though its application is limited due to the absence of models for many forest species. The foundational method for estimating Canopy Fuel Load (CFL) is destructive sampling, where tree samples are taken and dry weights are assessed. This data is then related to easily measured tree or stand attributes, leading to the creation of allometric models. These models, though simple, are species-specific and provide high predictive accuracy. Recently, remote sensing methods have been incorporated, but they too rely on these foundational models. As these allometric equations are simplistic and highly specific, they can be easily integrated into software tools. Current software tools, therefore, focus on these models, making them highly specialized and non-comparative. The specifics of these models, including their mathematical formulations and applicable tree species, are usually detailed in associated tables or databases.

M23: Models, methodologies and indices for fire risk assessment and fire damage estimation (chapter 2.5). Here an overview of the various models and methodologies used in research to assess wildfire risks is presented. Emphasis is given to the importance of understanding wildfire risks for safeguarding human populations and ecosystems. Several models are detailed, each with its mathematical expressions, inherent variables, and the quality criteria they had to meet to be considered significant. These models address different aspects of wildfire risks, such as ignition and spread probabilities, hazard, exposure, vulnerability, and spatial distribution. They also cater to different ecosystems, including the Wildland-Urban Interface areas. Critical steps in developing these models include data collection, variable distribution, model application, validation, and implementation. The models can be broadly categorized into ones based on long-term structural indices and short-term dynamic indices. A comprehensive table is also provided that describes various models, their methods, and the variables they consider. The chapter’s report concludes by highlighting the need for careful assessment to choose the most appropriate model for wildfire ignition modeling, given that each model has its limitations and prediction accuracies.

M24: Models of surface fuel load (chapter 2.6). The moisture content in different fuel classes, crucial for understanding fire behavior, varies seasonally, with higher levels in early spring and a decrease towards late summer and severe drought conditions. This aspect, among others, is encapsulated in Rothermel's estimation model, part of BehavePlus software, which accounts for factors like temperature, humidity, time of day, and slope to determine fine fuel moisture. Both live herbaceous and woody fuels significantly influence fire spread, their moisture content gauged by the water percentage in their weight and varying with vegetative growth stages. Key environmental factors, such as midflame wind speed and slope steepness, also impact fire behavior; the former represents average wind speeds within the fire's flames, and the latter the terrain's incline. The Rothermel surface spread model, critical in describing fire spread, has been adapted for use in R, enhancing fire behavior analysis. Accurate fire predictions demand a detailed fuel characteristics inventory, including the types and states of vegetation like grass, bushes, and forest understory. Tools like BehavePlus, NEXUS, FARSITE, and FlamMap model surface fire spread rates, requiring diverse inputs from basic fuel model codes to complex parameters like fuel load and moisture. Advanced modeling inputs delve deeper, covering specifics of fuels such as slash, shrub, and grass, providing a nuanced understanding essential for precise fire modeling.

M31: Models for predicting future Canopy Fuel Load (CFL) and Canopy Bulk Density (CBD) using Stand Basal Area Increment (chapter 2.7). The development and application of forest growth models have been constrained by the intricacy of field data requirements. Notwithstanding this challenge, several models have been put forward for basal area increment prediction. These models are gauged against a set of quality criteria which include relevance to core forest growth components, reference to pivotal forest growth factors, robustness in assessing basal area increment over time, applicability across diverse tree species, and operational simplicity. The methodologies for forest growth model development encompass pivotal steps such as comprehensive data collection, model application using diverse methods like Difference models, Linear and non-linear least squares models, and Artificial Neural Networks (ANN) models, followed by validation of the model's predictive accuracy. Several studies, as detailed, have delved into the specifics of wildfire risk assessment for various pine species, with each study offering its unique insights. Notably, while these models provide valuable insights into forest growth, they each come with their inherent simplifications and varying prediction accuracies. Furthermore, the assessment of these models hinges on factors such as suitability, prediction capacity, data requirements, and ease of software implementation. However, despite the existence of these models, there remains a conspicuous absence of software tools based on them. Given the mathematical simplicity of these models, the development of relevant software is deemed feasible.

M41: Models for climate change impact on forests (chapter 2.8). Forest growth modeling encompasses a broad spectrum of models, from empirical to process-based and hybrid forms. While empirical models, grounded in historical data, provide valuable insights, they can be constrained when applied to novel environmental conditions. Process-based models, on the other hand, emphasize physiological processes and their environmental dependencies. Hybrid models merge attributes from both types, aiming for enhanced accuracy and adaptability. Model M41 is an exemplar of this versatility, incorporating both process-based and hybrid attributes, evaluated against multiple parameters, from climate responsiveness to user-friendliness. A suite of 24 models, varying in their focus and approach, were meticulously assessed, and a Principal Component Analysis was employed to categorize them based on key criteria.

Complementing these models are a set of tools tailored to enhance their application and interpretation. Tools such as PnET-Succession, PnET-BGC, 3-PG Spatial, and BGC-MAN each offer unique functionalities, yet they come with their set of limitations, from data accessibility to model specificity. Nevertheless, these tools, when wielded judiciously, can significantly augment our understanding of forest dynamics, influencing policy-making and forest management strategies.

M42: Models for calculation of local weather conditions (chapter 2.9). Weather forecasting is a complex amalgamation of global meteorological models, further fine-tuned by national agencies to provide regional and local insights. While global models, like GFS, ECMWF, and ICON GLOBAL, offer a broad-spectrum view with varying resolutions, their accuracy diminishes as the forecast horizon extends, making them less reliable for long-term predictions. National meteorological agencies bridge this gap by downscaling these models, integrating real-time data from local weather stations to refine forecasts. This intricate interplay ensures that the forecasts are attuned to the unique climatic and geographical nuances of a region. Models like BOLAM, POSEIDON 2, and WRF, for instance, serve as pivotal tools for wildfire prevention and response, leveraging high-resolution data for precise insights. The confluence of these models, underpinned by a vast network of data sources from radiosondes to satellites, ensures that weather predictions are as accurate and actionable as possible.

M43: Models for estimating the effect of environmental factors on forest susceptibility to fire (chapter 2.10). The study critically analyzed two forest growth models, TREEMIG and CENTURY v4.0, each catering to specific ecological aspects. TREEMIG primarily focuses on tree species migration under climate change influences, incorporating factors like seed dispersal and competition. While its approach is holistic, it tends to simplify species-environment interactions by assuming unrestricted migration and neglecting genetic variability's role. Conversely, CENTURY v4.0 delves deep into ecosystem carbon and nitrogen dynamics, emphasizing soil organic matter and nutrient cycling. Despite its comprehensive framework, it demands intensive computational power and occasionally omits vital environmental factors. When assessed on parameters like suitability, prediction capacity, and ease of implementation, both models offer comparable performance, with CENTURY v4.0 slightly edging out TREEMIG. Notably, the analysis underscores the absence of supplementary tools for models under the M43 group.

M51: Models for wildfire ignition prediction (chapter 2.11). Various models are presented, each aiming to assess and predict wildfire ignition probabilities based on different factors. Model M51.1 by Hysa et al. (2018) utilizes the Analytical Hierarchy Process (AHP) and includes variables like distances to urban centers, rural settlements, roads, agricultural lands, and meteorological factors such as solar radiation, precipitation, temperature, and relative humidity. Model M51.2 from de Vasconcelos et al. (2001) employs Neural Networks and Logistic Regression. It emphasizes distances to various landmarks like roads, urban areas, agriculture, shrublands, and a variable capturing the aspect in terms of compass directions. Model M51.3 by Genton et al. (2006) introduces the k-function, focusing on the number of events like lightning strikes and human sources (e.g., railroads, arson) within a specific distance, and the type of fuels present in the area. Model M51.4 from Krawchuk et al. (2006) also uses Logistic Regression and highlights factors like deciduous canopy dominance, spruce canopy dominance, elevation, and specific indices related to fuel moisture and lightning. Model M51.5 by Syphard et al. (2008) employs Logistic Regression and examines variables like distances to developments, roads, and trails, vegetation types, the level of the Wildland-Urban Interface (WUI), and January temperature. Model M51.6 from Catry et al. (2009) utilizes Logistic Regression, focusing on population density, distances to roads, elevation, and various land cover classes.

M61: Enhancement of forest resilience through forest management treatments (chapter 2.12). Forest fire risk mitigation is a multifaceted endeavor that relies on a comprehensive understanding of environmental and forest (EF) factors and their dynamic interactions over time and space. This understanding is pivotal in determining forest management goals which consider forest productivity, risks, economic outcomes, and forest-derived goods requirements. A systematic classification, based on the work by Kaloudis (2008), highlights the influence of both biotic and abiotic EF factors. Various treatments, derived from forest practices and literature, aim at minimizing fire risks by managing vegetation and employing techniques like tree pruning, understory thinning, and fuelbreak construction. Notably, these treatments' efficacy varies based on the interplay of EF factors, emphasizing the importance of a holistic approach to forest management. This integrated strategy ensures that forests are not only protected from fires but also thrive as vital ecosystems, balancing ecological, economic, and social needs.

M62: Models of biodiversity index and ecological site classification (chapter 2.13). The realm of biodiversity and ecological modeling offers a plethora of tools and methods, each tailored to distinct aspects of environmental study. While models like the 'Calculating the number of species' and 'Shannon’s Diversity Index' provide insights into ecosystem size and species richness, they come with inherent methodological limitations. Similarly, mathematical models like the 'Emergy method' and 'NTM' provide innovative techniques for biodiversity assessment, but face challenges related to data accuracy and user accessibility. Empirical models, on the other hand, such as the 'Phytocentric approach' and 'Geocentric approach', emphasize factors affecting plant growth, but may be constrained in their applicability to specific forest scenarios. Moreover, the array of tools available, from the 'Ecological site classification' to 'GISCAME', cater to a wide range of applications, from carbon sequestration to biodiversity conservation. However, these tools are not without their restrictions, underscoring the need for rigorous conservation strategies, comprehensive databases, and context-specific applications. This diverse toolkit, though accompanied by certain limitations, offers researchers and conservationists a comprehensive framework for understanding and preserving biodiversity in varying ecological contexts.

M63: Models for the development of forest and landscape management (chapter 2.14). In the domain of ecological modeling, there is an extensive assortment of models, each tailored for specific applications and problem-solving. Mathematical models such as the 'Heuristic' and 'Linear programming' offer practical problem-solving methods, focusing on immediate goals and linear relationships, respectively. These models are notably integrated into software tools like ETÇAP, Monsu, and MELA, providing actionable insights for forest management. Semi-empirical models, like the 'Multicriteria decision analysis' and 'Data mining', delve into decision-making complexities and pattern extraction from vast data sets. Advanced mathematical models, such as the 'Monte Carlo method' and 'Bayesian method', incorporate probabilistic interpretations and prior distribution considerations, enhancing prediction accuracy. The realm also includes innovative models like the 'Artificial Neural Networks', which mimic human cognitive abilities to process information, and 'Growth simulators' that enable comprehensive ecosystem modeling. These models, when integrated with software tools like LEaRNForME and SIBYLA, provide a holistic approach to understanding and managing forest ecosystems. This diverse set of models showcases the breadth and depth of tools available to researchers and forest managers, empowering them to make informed and optimized decisions.

M71: Models for estimating air quality and corresponding risk for human health during forest fires (chapter 2.15). The extensive suite of relevant models presented showcases the depth and breadth of tools available for addressing various aspects of environmental monitoring and management. Within the realm of smoke dispersion and air quality, mathematical models such as VALBOX, VSMOKE, and CALPUFF provide insights into the transport and concentration of particulate matter and gaseous pollutants. While these models bring valuable capabilities, they also come with specific constraints, often related to their underlying assumptions or computational requirements. For instance, VALBOX assumes uniform emissions within its defined volume, and models like WFDS and FIRETEC are computationally intensive due to their high-resolution approach. Emission estimation models, like BURNUP and CONSUME, focus on predicting fuel consumption, heat release, and pollutant emissions from fires, yet their applicability can be limited by specific regional conditions. Additionally, air quality indices such as EAQI and US AQI offer real-time insights into regional and city-level air quality, aiding public awareness and policy decisions. However, they too have limitations in terms of the coverage and granularity of the data they provide. Overall, while these models and tools offer a comprehensive approach to understanding and managing air quality and fire-related emissions, they underscore the importance of selecting the right tool for the specific context and understanding their inherent limitations.

M72: Models to simulate and support evacuation needs due to forest fire event (chapter 2.16). The field of evacuation route planning and safe zone estimation in the context of wildfires is rich with a variety of mathematical, empirical, and review models. From the presented models for evacuation planning, it's evident that many focus on predicting fire spread, traffic behavior, and estimating the safest and quickest routes for evacuation. These models, such as those proposed by Wang et. al.(2014) and Beloglazov et. al. (2016), rely heavily on mathematical formulations to provide dynamic and real-time solutions. However, they also come with specific restrictions, such as sensitivity to the accuracy of fire simulation outputs or assumptions about vehicular movement and resident behaviors. The WUI-NITY model stands out for its focus on simulating and visualizing human behavior during evacuations but lacks route suggestions. On the other hand, models like ESCAPE by Maranghides and Link (2023) offer more holistic approaches, emphasizing community collaboration and pre-fire planning. In the realm of safe zone estimation, the models by Butler and Forthofer (2002) and Butler and Cohen (1998) provide empirical methods to estimate safe distances from fires. However, these too come with their set of limitations, highlighting the importance of considering multiple factors and real-world variables when planning for wildfire evacuations. Overall, while these models offer valuable insights, it's essential to recognize their constraints and ensure they're used in appropriate contexts to maximize their efficacy.

M82: Models for soil erosion, including also geomorphological and topographic models as well as models focused on hydraulics (chapter 2.17-2.19). Soil erosion is a pressing environmental issue affected by a myriad of both natural and anthropogenic factors. Its study and monitoring have been greatly enhanced by the advances in geospatial technologies, notably remote sensing, which have enabled the detailed observation of various landforms and the erosion processes that shape them. The last few decades have seen an increasing understanding of the detrimental impacts of soil erosion, not just on the environment, but also on the long-term sustainability of soils. Consequently, this has spurred the development and application of strategies to combat these erosive forces. Modeling plays a paramount role in understanding and quantifying soil erosion. Over the past half-century, the integration of GIS and remote sensing data has significantly propelled the development of erosion models, offering a plethora of tools that vary in complexity and input requirements. Erosion modeling, as elucidated by numerous research works, is essential for grasping erosion processes, especially when direct experimental observations are not feasible. Models generally fall into three categories: empirical, conceptual, and physically-based. Empirical models, rooted in statistical relationships, are simple and require minimal data, making them suitable for areas with limited datasets. However, their primary limitation is their specificity to the region of their development. Conceptual models combine elements of the other two and focus on estimating sediment yield, offering a more holistic view of a catchment. Physically-based models, on the other hand, derive from fundamental physical laws and are more comprehensive, though they come with the challenges of over-parameterization and increased complexity.

M85: Soil quality indices (chapter 2.20). The study and assessment of soil quality and contamination are vital for understanding the environmental health of a region and the potential risks posed by pollutants. To this end, various indices and models have been developed to quantify and evaluate the extent of soil contamination. The presented models range from Soil Quality Index (SQI) that indicates overall soil health to more specialized indices like the Geoaccumulation Index (I_geo) and Single Pollution Index (PI) that gauge the accumulation of specific heavy metals in the soil. Empirical models like the Geoaccumulation Index or the Contamination Factor (CF) rely on observed data and statistical relationships to describe soil conditions. These models are often simple, making them suitable for quick assessments, especially in areas with limited data. However, their primary limitation is often their specificity to the region where they were developed. More advanced models, such as the Multi-element contamination (MEC) or the Contamination security index (CSI), incorporate multiple variables and often consider various heavy metals, providing a comprehensive overview of soil contamination. These models often require a more extensive dataset and might incorporate weightage systems or reference values to assess the contamination severity.

M86: Desertification indices (chapter 2.21). Desertification monitoring and assessment are paramount for understanding land degradation and implementing appropriate mitigation measures. Various models and methodologies, both empirical and mathematical, have been developed to evaluate desertification, each with specific capabilities and limitations. The models range from the widely recognized European Environment Agency's ESA & RDI (Kosmas et al., 1999) for mapping Environmentally Sensitive Areas to more region-specific models like those tested in China, Lebanon, and Brazil. These models often utilize NDVI derived from satellite imagery, such as Landsat or MODIS, to assess vegetation health as an indicator of desertification. The incorporation of GIS further enhances the spatial assessment capabilities of these models. However, the choice of model largely depends on the specific region of interest, available datasets, and the granularity of assessment required. While some models are broad in their applicability, others are tailored for specific regions or use specific indicators, making them less universally applicable. Regardless of the chosen model, continuous monitoring, validation, and model refinement are essential to ensure accurate and timely desertification assessments.

Together, these chapters provide a comprehensive view of both the theoretical and practical aspects of forest protection against wildfires and integrative forest management, with a view to building environmentally sustainable and resilient forests, serving as an invaluable resource for researchers, policymakers, and forest management professionals alike.

4. References

3MON. 2023a. GINA Central. Available online: https://3mon.sk/en/portfolio/item/gina-central-station/. (Access 07.09.2023)

3MON. 2023b. GINA Tablet. Available online: https://3mon.sk/en/portfolio/item/navigation-system-gina-tablet/. (Access 07.09.2023)

3MON. 2023c. GINA Hems. Available online: https://3mon.sk/en/portfolio/item/navigation-system-gina-hems/. (Access 07.09.2023)

3MON. 2023d. GINA GO. Available online: https://3mon.sk/en/portfolio/item/navigation-system-gina-go/. (Access 07.09.2023)

Abrahim, G. M. S., & Parker, R. J. (2008). Assessment of heavy metal enrichment factors and the degree of contamination in marine sediments from Tamaki Estuary, Auckland, New Zealand. *Environmental Monitoring and Assessment*, *136*, 227–238.

Achtemeier, G. L., Goodrick, S. A., Liu, Y., Garcia-Menendez, F., Hu, Y., & Odman, M. T. (2011). Modeling smoke plume-rise and dispersion from southern United States prescribed burns with Daysmoke. Atmosphere, 2(3), 358-388.

Adab H, Kanniah KD, Solaimani K (2013) Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. *Nat Hazards* 65: 1723–1743.

Adamu, C. L., & Nganje, T. N. (2010). Heavy metal contamination of surface soil in relationship to land use patterns: A case study of Benue State, Nigeria. *Materials Sciences and Applications*, *1*, 127–134.

Agee, J. K., Bahro, B., Finney, M. A., Omi, P. N., Sapsis, D. B., Skinner, C. N., van Wagtendonk, J. W., Phillip Weatherspoon, C. (2000). The Use of Shaded Fuelbreaks in Landscape Fire Management. Forest Ecology and Management, 127 (1-3): 55-66.

Agee, JK and Skinner, CN (2005). Basic Principles of Forest Fuel Reduction Treatments. Forest Ecology and Management, 211 (1-2): 83-96.

Ager, A.A., Finney, M.A. Application of wildfire simulation models for risk analysis. Paper presented at the EGU General Assembly Conference Abstracts. 2009.

Ager, A.A., Vaillant, N.M., Finney, M.A. Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. Journal of Combustion, 2011, 19. doi:10.1155/2011/572452

Ahmad S, Ali A, Ahmed HU, Huang Y, Lu P., (2023). Evaluating Traffic Operation Conditions during Wildfire Evacuation Using Connected Vehicles Data. Fire.; 6(5):184. https://doi.org/10.3390/fire6050184

Ahtisoski, A., Salminen, H., Hökkä, H., Kojola, S., Penttilä, T. Optimising stand management on peatlands: The case of northern Finland. In Can J For Res., 2012, 42:247–59.

Ahtisoski, A., Salminen, H., Ojansuu R, Hynynen, J., Kärkkäinenen, K., Haapanen, M. Optimizing stand management involving the effect of genetic gain: Preliminary results for Scots pine in Finland. In Can J For Res., 2013, 43:299–305.

AirNow.gov (2023). Air Quality Index (AQI) Basics. https://www.airnow.gov/aqi/aqi-basics/

Al-Anbari, R., Abdul Hameed, M. J., Obaidy, A. I., & Fatima, H. A. A. (2015). Pollution loads and ecological risk assessment of heavy metals in the urban soil affected by various anthropogenic activities. *International Journal of Advanced Research*, *2*, 104–110.

Albini, F. A. and Baughman, R. G. 1979. Estimating windspeeds for predicting wildland fire behavior. Res. Pap. INT-221. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 12 p.

Albini, F. A., & Reinhardt, E. D. (1995). Modeling ignition and burning rate of large woody natural fuels. International Journal of Wildland Fire, 5(2), 81-91.

Albini, F.A. (1976). Estimating Wildfire Behavior and Effects. General Technical Report, INT-30, U.S.A. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT.

Albini, F.A. Computer-based models of wildland fire behavior: a user's manual. Odgen, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1976b.

Albini, F.A. Estimating wildfire behavior and effects. Gen. Tech. Rep. INT-GTR-30. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, 92 p., 1976.

Albini, F.A. Estimating wildfire behavior and effects. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-30. 1976a.

Albini, F.A. Potential spotting distance from wind-driven surface fires. Research Paper INT-309. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1983a, 27 p.

Albini, F.A. Spot fire distance from burning trees-a predictive model. General Technical Report INT-GTR-56. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1979, 73 p.

Albini, F.A. Spot fire distance from isolated sources – extensions of a predictive model. Research Note INT-309. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1981, 10 p.

Albini, F.A. Transport of firebrands by line thermals. In Combustion Science and Technology, 1983b, 32: 277–288. doi:10.1080/0010220830.

Albini, F.A., Alexander, M.E., Cruz, M.G. A mathematical model for predicting the maximum potential spotting distance from a crown fire. In International Journal of Wildland Fire, 2012, 21(5):609-627.

Alexander, M.E., Cruz, M.G. Are the applications of wildland fire behaviour models getting ahead of their evaluation again? In Environ. Model. Softw., 2013, 41:65–71. doi:10.1016/j.envsoft.2012.11.001.

Alexander, M.E., Cruz, M.G., Lopes, A.M.G. CFIS: A software tool for simulating crown fire initiation and spread. In Forest Ecology and Management,2006, 234S: S133.

Alexander, M.E., Stefner, C.N., Mason, J.A., Stocks, B.J., Hartley, G.R., Maffey, M.E., Wotton, B.M., Taylor, S.W., Lavoie, N. and Dalrymple, G.N. 2004. Characterizing the jack pine–black spruce fuel complex of the International Crown Fire Modelling Experiment. Canadian Forest Service Information Report NOR-X-393.

Alvelos, F. Mixed integer programming models for firefighting. In Proceedings of the International Conference on Computational Science and Its Applications, Melbourne, Australia, 2–5 July 2018, Springer: Berlin/Heidelberg, Germany, 2018, pp. 637–652.

Amacher, M. C., O'neill, K. P., & Perry, C. H. (2007). *United States Department of Agriculture Soil Vital Signs: A New Soil Quality Index (SQI) for Assessing Forest Soil Health*. http://www.fs.fed.us/rmrs/

Amidon, E.L., Akin, G.S. Dynamic programming to determine optimum levels of growing stock. In For Sci. 1968, 14(3):287–91.

Anderson, G. K., Sandberg, D. V., & Norheim, R. A. (2004). Fire Emission Production Simulator (FEPS) User's Guide. USDA Forest Service, 99.

Anderson, H.E. Heat transfer and fire spread. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, Research Paper INT-RP-69, 1969.

Anderson, H.E. Heat transfer and fire spread. Res. Pap. INT-RP-69. Ogden, Utah: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, 1969, 20 p.

Andrenelli, M.C., Colle, G., Galvagni, D., Giannetti, F., Gregori, E., Scrinzi, G., Zorn, G. Assessing the protective role of the forest cover against hydrogeological disturbances:a GIS-based tool for forest planning - IUFRO International Conference: "NATURAL HAZARDS AND NATURAL DISTURBANCES IN MOUNTAIN FORESTS" - Trento, ITALY (September 18th-21th, 2007).

Andrews, P. L. 1986. BEHAVE: Fire behavior prediction and fuel modeling system—BURN Subsystem, Part 1. Gen. Tech. Rep. INT-194. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 130 p.

Andrews, P.L. 2018. The Rothermel surface fire spread model and associated developments: a comprehensive explanation. Gen. Tech. Rep. 121 RMRS-GTR-371.

Andrews, P.L. Current status and future needs of the BehavePlus Fire Modeling System. In International Journal of Wildland Fire, 2014, 23(1): 21-33. doi: 10.1071/WF12167.

Andrews, P.L. Do you BEHAVE? Application of the BehavePlus fire modeling system. Proceedings of 3rd Fire Behavior and Fuels Conference, October 25-29, 2010, Spokane, Washington, USA, 17 p.

Andrews, P.L., Bevins, C.D., Seli, R.C. BehavePlus fire modeling system, version 4.0: User's guide. USDA Forest Service, Rocky Mountain Research Station, General Tech. Rep. RMRS-GTR-106WWW, 2008, 132 pp.

Andrews, P.L., Heinsch, F.A., Schelvan, L. How to generate and interpret fire characteristics charts for surface and crown fire behavior. Fort Collins, CO: USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-253, 2011.

Andrews, P.L., Rothermel, R.C. Charts for interpreting wildland fire behavior characteristics. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-131, 1982.

Ang Chen, Xiuchun Yang, Jian Guo, Xiaoyu Xing, Dong Yang, Bin Xu, Synthesized remote sensing-based desertification index reveals ecological restoration and its driving forces in the northern sand-prevention belt of China, Ecological Indicators, Volume 131, 2021, 108230, ISSN 1470-160X, https://doi.org/10.1016/j.ecolind.2021.108230.

ArcGIS Solutions. 2023. Introduction to Fire Incident Dashboard. Available online: https://doc.arcgis.com/en/arcgis-solutions/latest/reference/introduction-to-fire-incident-dashboard.htm. (Access 14.09.2023)

Arjan de Bruijn, Eric J. Gustafson, Brian R. Sturtevant, Jane R. Foster, Brian R. Miranda, Nathanael I. Lichti, Douglass F. Jacobs. (2014). Toward more robust projections of forest landscape dynamics under novel environmental conditions: Embedding PnET within LANDIS-II. Ecological Modelling, Volume 287, 10 September, Pages 44–57.

Arnold, J. G., and Fohrer, N. (2005). “SWAT 2000: Current capabilities and research opportunities in applied watershed modeling.”Hydrol. Process., 19(3), 563–572.

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., Van Griensven, A., Van Liew, M.W., Kannan, N., Jha, M.K., (2012). SWAT: Model use, calibration, and validation. Trans. ASABE 55, 1491–1508. doi:10.13031/2013.42259.

Augustynczik, A.L.D., Arce, J.E., Silva, A.C.L.. Implementing minimum area harvesting blocks in an optimized forest planning model. In Rev. Árvore, 2017, 41:2-8. doi: 10.1590/1806-90882017000100018.

Augustynczik, A.L.D., Yousefpour, R., Rodriguez, L.C.E., Hanewinkel, M. Conservation costs of retention forestry and optimal habitat network selection in southwestern Germany. In Ecol. Econ., 2018, 148:92-102. doi: 10.1016/j.ecolecon.2018.02.013.

Avendaño Salas, C., Sanz Montero, M. E., Cobo Rayán, R., & Gómez Montaña, J. L. (1997). Sediment yield at Spanish reservoirs and its relationship with the drainage area. 19th Symposium of Large Dams, 863–874.

Avwunudiogba, A., & Hudson, P. F. (2014). A review of soil erosion models with special reference to the needs of humid tropical mountainous environments. European Journal of Sustainable Development, 3(4), 299–310. http://dx.doi.org/ 10.14207/ejsd.2014.v3n4p299.

Bachelet, D., Lenihan, J.M., Daly, C., Neilson, R.P. (2000). Interactions between Fire, Grazing and Climate Change at Wind Cave National Park, SD. Ecological Modelling, 134 (2-3): 229-244.

Baeza, M. J., De Luis, M., Raventos, J., Escarre, A. (2002). Influencing Factors Fire Behavior in Shrublands of Different Stand Ages and their Implications for Using Prescribed Burning to Reduce Wildfire Risk. Journal of Environmental Management, 65 (2): 199-208.

Baeza, M. J., Raventos, J., Escarre, A., Vallejo, VR (2003). The Effect of Shrub Clearing on the Control of Fire-Prone Species Ulex Parviflorus. Forest Ecology and Management, 186 (1-3): 47-59.

Bakhshaii, A., Johnson, E.A. A review of a new generation of wildfire–atmosphere modeling. In Can. J. For. Res. 2019, 49:565–574.

Baldwin VCJr., Peterson, K. D., Clark III, A., Ferguson, R. B., Strub, M. R., Bower, D. R. (2000). The Effects of Spacing and Thinning on the Stand and Tree Characteristics of the 38-Year-Old Loblolly Pine. Forest Ecology and Management, 137 (1-3): 91-102.

Barreiro, S., Garcia-Gonzalo, J., Borges, J. G., M. Tomé, M., Marques, S. SADfLOR Tutorial. A Web-based Forest and Natural Resources Decision Support System (Work in progress), FORCHANGE, ISA, Lisboa, 2013, 39 p.

Başkent, E.Z., Başkaya, Ş., Terzioğlu, S. 2008. Developing and implementing participatory and ecosystem based multiple use forest management planning approach (ETÇAP): Yalnızçam case study. In Forest Ecology and Management, 2008, 256:798–807.

Baskent, E.Z., Keles, S. Spatial forest planning: a review. In Ecol. Model., 2005, 188:145-173. doi: 10.1016/j.ecolmodel.2005.01.059.

Baskent, E.Z., Keles, S. Spatial forest planning: a review. In Ecol. Model., 2005, 188:145-173. doi: 10.1016/j.ecolmodel.2005.01.059.

Baskerville, G. 1972. Use of logarithmic regression in the estimation of plant biomass. *Can. J. Forest Res.* 2:49–53.

Battaglia, M., Sands, P., White, D., & Mummery, D. (2004). CABALA: A linked carbon, water, and nitrogen model of forest growth for silvicultural decision support. Forest Ecology and Management, 193(1), 251–282. https://doi.org/10.1016/j.foreco.2004.01.033

Bayat, M., Pukkala, T., Namiranian, M., Zobeiri, M. Productivity and optimal management of the uneven-aged hardwood forests of Hyrcania. In Eur J For Res., 2013, 132:851–64.

Bayham, J., Yoder, J.K. Resource allocation under fire. In Land Econ., 2020, 96: 92–110.

Baysal,̇ I. 2021. Vertical crown fuel distributions in natural calabrian pine (*Pinus brutia Ten.) stands. Croat. J. For. Eng.* 42:301-312.

Beasley, D.B., Huggins, L.F. and Monke, E.J., (1989). ANSWERS: a model for watershed planning. Transactions of ASAE, 23(4): 938-944.

Beck, M.B. (1987). Water quality modeling: A review of the analysis of uncertainty. Water Resour. Res., 23, 1393–1442.

Behrisch M., Bieker L., Erdmann J.,Krajzewicz D. (2011), SUMO – Simulation of Urban MObility An Overview, *The Third International Conference on Advances in System Simulation* https://sumo.dlr.de/docs/index.html

Beloglazov, A., Almashor, M., Abebe, E., Richter, J., & Steer, K. C. B. (2016). Simulation of wildfire evacuation with dynamic factors and model composition. *Simulation Modelling Practice and Theory*, *60*, 144-159.

Belval, E.J., Stonesifer, C.S., Calkin, D.E. Fire suppression resource scarcity: Current metrics and future performance indicators. In Forests, 2020, 11:217.

Belval, E.J., Wei, Y. Modeling Ground Firefighting Resource Activities to Manage Risk Given Uncertain Weather. In Forests, 2019, 10:1077.

Belval, E.J., Wei, Y., Bevers, M. A mixed integer program to model spatial wildfire behavior and suppression placement decisions. In Can. J. For. Res., 2015, 45:384–393.

Belval, E.J., Wei, Y., Bevers, M. A stochastic mixed integer program to model spatial wildfire behavior and suppression placement decisions with uncertain weather. In Can. J. For. Res., 2016, 46:234–248.

Bettinger, P., Boston, K., Siry, J.P., Grebner, D.L. Forest Management and Planning. Academic Press: Elsevier, 2017, p. 362.

Bettinger, P., Sessions, J. Spatial Forest planning: to adopt, or not to adopt? In J. For., 2003, 101:24-29. doi:10.1093/jof/101.2.24.

Bevins, C.D., 1996. fireLib user manual and technical reference. Available online: http://www.fire.org/ firelb/doc.html. (Accessed 03.09.23)

Blum, C., Blesa, M.J., García-Martínez, C., Rodríguez, F.J., Lozano, M. The firefighter problem: Application of hybrid ant colony optimization algorithms. In Proceedings of the European Conference on Evolutionary Computation in Combinatorial Optimization, Granada, Spain, 23–25 April 2014, Springer: Berlin/Heidelberg, Germany, 2014, pp. 218–229.

Bodaghi, B., Palaneeswaran, E., Shahparvari, S., Mohammadi, M. Probabilistic allocation and scheduling of multiple resources for emergency operations, a Victorian bushfire case study. In Comput. Environ. Urban Syst. 2020, 81:101479.

Bogdos, N., Manolakos, E.S. A tool for simulation and geo-animation of wildfires with fuel editing and hotspot monitoring capabilities. In Environmental Modelling & Software, 2013, 46:182-195. Doi: 10.1016/j.envsoft.2013.03.009.

Borges, P.J., Fragoso, R., Garcia-Gonzalo, J., Borges, J.G., Marques, S., Lucas, M. R. 2010. Assessing impacts of Common Agricultural Policy changes on regional land use patterns with a decision support system: An application in Southern Portugal. In Forest Policy and Economics, 2010, 12(2):111–120. doi: 10.1016/j.forpol.2009.09.002.

Bradshaw, L., McCormick, E. FireFamily Plus user's guide, Version 2.0. Gen. Tech. Rep. RMRS-GTR-67WWW. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2000.

Brandt, J. and Geeson, N. (2015). Desertification indicator system for Mediterranean Europe. In Monitoring and Modelling Dynamic Environments (eds A.P. Dykes, M. Mulligan and J. Wainwright). https://doi.org/10.1002/9781118649596.ch6.

Bravo, F., Fabrika, M., Ammer, Ch., Barreiro, S., Bielak, K., Coll, L., Fonseca, T. et al. Modelling approaches for mixed forests dynamics prognosis. Research gaps and opportunities. In Forest Systems, 2019, 28(1):eR002.

Brown, J. K., Oberheu, R. D. and Johnston, C. M. 1982. Handbook for inventorying surface fuels and biomass in the Interior West. Gen. Tech. Rep. INT-129. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 48 p.

Bugmann, H. K. M. (1996). A simplified forest model to study species composition along climate gradients. Ecology, 77(7), 2055–2075.

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J. W., & Brussaard, L. (2018). Soil quality – A critical review. *Soil Biology and Biochemistry*, *120*, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030

Burkhart, H.E. and Tomé, M. 2012. Modeling forest trees and stands. Springer, Dordrecht.

Butler and Forthofer, (2002). https://www.frames.gov/documents/behaveplus/publications/Butler_and_Forthofer_2002_WM_SafetyZones_ocr.pdf

Butler, B. W., & Cohen, J. D. (2000). Field verification of a firefighter safety zone model. Proceedings of the 2000 international wildfire safety summit, 10-12.

Butler, B., Cohen, J.D. Firefighter Safety Zones: A Theoretical Model Based on Radiative Heating. In International Journal of Wildland Fire, 1998, 8(2):73-77. doi: 10.1071/WF9980073.

Butler, B.W., Cohen, J.D. An analytical evaluation of firefighter safety zones. In '13th Fire and Forest Meteorology Conference', 27–31 October 1996, Lorne, Vic., Australia. (Ed. J Greenlee) pp. 117–121.

Butler, B.W., Cohen, J.D. Firefighter safety zones: a theoretical model based on radiative heating. In International Journal of Wildland Fire, 1998a, 8:73–77.

Butler, B.W., Cohen, J.D. Firefighter safety zones: how big is big enough? In Fire Management Notes, 1998b, 58:13–16.

Butler, B.W., Finney, M.A., Andrews, P.L., Albini, F.A. A radiation-driven model for crown fire spread. In Canadian Journal of Forest Research, 204, 34(8):1588-1599.

Butler, BW and Cohen, JD (1998). Firefighter Safety Zones: A Theoretical Model Based on Radiative Heating. International Journal of Wildland Fire, 8 (2): 73-77.

Butler, BW and Cohen, JD (1998). Firefighter Safety Zones: How Big Is Big Enought? Fire Management Notes, 58 (1): 13-16.

Byram, G. M. 1959. Combustion of forest fuels. In: Forest fire: control and use, 2nd edition. New York: McGraw-Hill: chapter 1: 61–89.

Byram, G.M. 1959. Combustion of forest fuels. Pages 61-89 In: Davis, K. P., editor. Forest fire: control and use. New York, NY: McGraw-Hill.

Byun, D., & Schere, K. L. (2006). Review of the governing equations, computational algorithms, and other components of the Models-3 Community Multiscale Air Quality (CMAQ) modeling system. Applied mechanics reviews, 59(2), 51-77.

Byungdoo, L., Yohan, L., Lee, M.B., Albers, H.J. Stochastic Simulation Model of Fire Occurrence in the Republic of Korea. In J. Korean For. Soc. 2011, 100:70–78.

Campbell, M.J., Dennison, P.E., Butler, B.W. Safe Separation Distance Score: A New Metric for Evaluating Wildland Firefighter Safety Zones Using Lidar. In Int. J. Geogr. Inf. Sci., 2017, 31:1448–1466.

Campbell, M.J., Dennison, P.E., Thompson, M.P., Butler, B.W. Assessing Potential Safety Zone Suitability Using a New Online Mapping Tool. In Fire, 2022, 5:5. doi:10.3390/fire5010005.

Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M, Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S. Biodiversity loss and its impact on humanity. In Nature, 2012, 486(7401):59-67. doi: 10.1038/nature11148.

Carnus, J.M., Parrotta, J., Brockerhoff, E., Arbez, M., Jactel, H., Kremer, A., Lamb, D., O'Hara, K., Walter, B. Planted forest and biodiversity. In For. Ecol., 2006, 104(2):65-77.

Carter, MC and Foster, CD (2004). Prescribed Burning and Productivity in Southern Pine Forests: A Review. Forest Ecology and Management, 191 (1/3): 93-109.

Carton H. (2020). Wildfire Evacuation Modelling Coupling Traffic and Fire Behaviour. Proceedings of The National Conference on Undergraduate Research (NCUR) 2020 Montana State University, Bozeman, MT March 26 – 28, 2020. http://libjournals.unca.edu/ncur/wp-content/uploads/2020/12/3177-Carton-Hannah-FINAL-1.pdf

Cass, S. (2005). "Moral Heuristics". In The Behavioral and Brain Sciences, 2005, 28(4):531–542. doi:10.1017/S0140525X05000099.

Castaño-Santamaría, J., Crecente-Campo, F., Fernández-Martínez, J.L., Barrio-Anta, M. Obeso, J.R. Tree height prediction approaches for uneven-aged beech forests in northwestern Spain. In Forest Ecology and Management, 2013, 307(11):63-73.

Catry FX, Rego FC, Bação FL, Moreira F (2009) Modeling and mapping wildfire ignition risk in Portugal. Int J Wildland Fire 18:921–931.

Cavalante de Jesus França, L., Acerbi Júnior, F.W., Jarochinski e Silva, C.S., Augusto Ussi Monti, C.A., Ferreira, T.C., de Oliveira Santana, C.J., Rezende Gomide, L. Forest landscape planning and management: A state-of-the-art review. In Trees, Forests and People, 2022, 8:100275.

Chan, H., Tran-Thanh, L., Viswanathan, V. Fighting wildfires under uncertainty: A sequential resource allocation approach. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, Yokohama, Japan, 11–17 July 2020, pp. 4322–4329.

Chase, C.H. Spot fire distance equations for pocket calculators. Research Note INT-RN-310. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1981, 21 p.

Chase, C.H. Spotting distance from wind-driven surface fires-extensions of equations for pocket calculators. Research Note INT-RN-346. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, 1984, 21 p.

Chertov, O.G. Komarov, A.S., Nadporozhskaya, M.A., Bykhovets, S.A., Zudin, S.L. ROMUL – a model of forest soil organic matter dynamics as a substantial tool for forest ecosystem modelling. In Ecological Modelling, 2001, 138(1-3):289-308.

Chertov, O.G. Komarov, A.S., Tsiplianovsky, A.V. 1999. A combined simulation model of Scots pine, Norway spruce and Silver birch ecosystems in European boreal zone. In Forest Ecology and Management, 1999, 116:189-206.

Chertov, O.G., Komarov, A.S. 1997. SOMM -- a model of soil organic matter dynamics. In Ecological Modelling, 1997, 94(2-3):177-189.

Chesebrough, R. 2023. Predicting Forest Fires Using PyTorch. Available online: https://medium.com/intel-analytics-software/predict-forest-fires-using-pytorch-333e3d6f01ac. (Accessed 09.07.2023)

Chopra, P., Sharma, R.K., Kumar, M. Regression models for the prediction of compressive strength of concrete with & without fly ash. In International Journal of Latest Trends in Engineering and Technology, 2014, 3: 400–406.

Chow, J.Y., Regan, A.C. Resource location and relocation models with rolling horizon forecasting for wildland fire planning. In INFOR Inf. Syst. Oper. Res., 2011, 49:31–43.

Chuvieco E, Congalton RG (1989) Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sens Environ* 29:147–159.

Chuvieco E, Yebra M, Martino S, Thonicke K, Gómez-Giménez M, San-Miguel J, Oom D, Velea R, Mouillot F, Molina JR, Miranda AI, Lopes D, Salis M, Bugaric M, Sofiev M, Kadantsev E, Gitas IZ, Stavrakoudis D, Eftychidis G, Bar-Massada A, Neidermeier A, Pampanoni V, Pettinari ML, Arrogante-Funes F, Ochoa C, Moreira B, Viegas D (2023) Towards an Integrated Approach to Wildfire Risk Assessment: When, Where, What and How May the Landscapes Burn. *Fire* 6(5):215.

Cioffi C., Luke S., Panait L., Sullivan M. K., Balan G. C. (2005), *SIMULATION: Transactions of The Society for Modeling and Simulation International 81(7):517-527.* Available online: https://cs.gmu.edu/~eclab/projects/mason/

Clifton, Ch. 2010. "Encyclopædia Britannica: Definition of Data Mining". Available online: https://www.britannica.com/summary/data-mining.

Coen, J. L. Some new basics of fire behavior. In Fire Management Today, 2011, 71(1):37-42.

Coen, J.L. Simulation of the Big Elk Fire using coupled atmosphere–fire modeling. In International Journal of Wildland Fire, 2005, 14(1):49-59. doi: 10.1071/WF04047.

Coen, J.L., Cameron, M., Michalakes, J., Patton, E.G., Riggan, P.J., Yedinak, K.M. WRF-Fire: Coupled Weather–Wildland Fire Modeling with the Weather Research and Forecasting Model. In Journal of Applied Meteorology and Climatology, 2013, 52(1):16-38. doi: 10.1175/JAMC-D-12-023.1.

Cohen JD, Deeming DE (1985) The National Fire Danger Rating System: basic equations. USDA and Forest Service, Pacific Southwest Forest and Range Experiment Station. Gen Tech Rep PSW-82.

Collalti, A., Thornton, P. E., Cescatti, A., Rita, A., Borghetti, M., Nolè, A., Trotta, C., Ciais, P., & Matteucci, G. (2019). The sensitivity of the forest carbon budget shifts across processes along with stand development and climate change. Ecological Applications, 29(2), e01837.

Condés S, Sterba H (2008) Comparing an individual tree growth model for *Pinus halepensis* Mill in the Spanish region of Murcia with yield tables gained from the same area. *Eur J For Res* 127:253–261.

Constantino, M., I. Martins, I., Borges, J.G. A new mixed-integer programming model for harvest scheduling subject to maximum area restrictions. In Oper. Res., 2008, 56(3):542-551. doi: 10.1287/opre.1070.0472.

CORDIS. (1 November 2023). Preventing and fighting extreme wildfires with the integration and demonstration of innovative means | Programme | H2020 | CORDIS | European Commission. Publication Office/CORDIS. Retrieved from https://cordis.europa.eu/programme/id/H2020_LC-GD-1-1-2020/en

Cormen, T.H., Leiserson, C.E., RivesR t,.L., Stein, C. Introduction to Algorithms (2nd ed.). MIT Press & McGraw–Hill, 2001, pp. 344. ISBN 0-262-03293-7.

Cruz, M.G., Alexander, M.E. and Wakimoto, R.H. 2003. Assessing canopy fuel stratum characteristics in crown fire prone fuel types of western North America. *Int. J. Wildland Fire* 12: 39–50.

Cruz, M.G., Alexander, M.E., Wakimoto, R.H. 2003. Assessing the probability of crown fire initiation based on fire danger indices. In For. Chron., 2003, 79:976983.

Cruz, M.G., Alexander, M.E., Wakimoto, R.H. Assessing canopy fuel stratum characteristics in crown fire prone fuel types of western North America. In International Journal of Wildland Fire, 2003, 12(1):39-50.

Cruz, M.G., Alexander, M.E., Wakimoto, R.H. Development and testing of models for predicting crown fire rate of spread in conifer forest stands. In Can. J. For. Res., 2005, 35:1626–1639.

Cruz, M.G., Alexander, M.E., Wakimoto, R.H. Modelling the likelihood of crown fire occurrence in conifer forest stands. In For. Sci., 2004, 50:640–658.

Cruz, M.G., Gould, J.S., Alexander, M.E., Sulivan, A.L., McCaw, W.L., Mathews, S. A Guide to Rate of Fire Spread Models for Australian Vegetation. (CSIRO) Land and Water Flagship, Canberra, ACT, and AFAC Melbourne, Vic, 2015, 125pp.

Curt, T., Fréjaville, T. Wildfire Policy in Mediterranean France: How Far Is It Efficient and Sustainable? In Risk Anal., 2017, 38: 472–488.

Curtis, F.H. Linear programming the management of a forest property. In J. For., 1962, 60(9):611-616. doi: 10.1093/jof/60.9.611.

da Silva, I.N., Spatti, D.H., Flauzino, R.A., Bartocci Liboni, L.H., dos Reis Alves, S.F. Artificial Neural Networks: A Practical Course. Springer Nature eBook, 1st ed., 2017, 307 p. doi: 10.1007/978-3-319-43162-8.

Da Silva, R. M., Santos, C. A. G., & Silva, A. M. (2014). PREDICTING SOIL EROSION AND SEDIMENT YIELD IN THE TAPACURÁ CATCHMENT, BRAZIL. Journal of Urban and Environmental Engineering, 75–82. https://doi.org/10.4090/juee.2014.v8n1.075082

de Coligny F. Efficient Building of Forestry Modelling Software with the Capsis Methodology. In: Fourcaud T, Zhang XP, eds. Plant Growth Modeling and Applications. Proceedings of PMA06. Los Alamitos, California: IEEE Computer Society, 2007, pp. 216-222.

De Roo, A.P.J., Wesseling, C.G., Jetten, V.G., Ritsema, C.J., (1996). LISEM: a physicallybased hydrological and soil erosion model incorporated in a GIS. Appl. Geogr. Inf. Syst. Hydrol. water Resour. Manag. Proc. HydroGIS'96 Conf. Vienna, 1996, pp. 395–403.

De Roo, APJ, and Jetten, VG, (1999). Calibrating and validating the LISEM model for two data sets from the Netherlands and South Africa: Catena 37: 477-493.

de Vasconcelos MJP, Silva S, Tomé M, Alvim M, Pereira JMC (2001) Spatial prediction of fire ignition probabilities: comparing logistic regression and neural networks. Photogramm Eng Remote Sens 67:73–83.

De Vente, J., Poesen, J. (2005). Predicting soil erosion and sediment yield at the basin scale: scale issues and semi-quantitative models. Earth Sci. Rev., 71 (2005), pp. 95-125.

Deckmyn, G., Verbeeck, H., Op de Beeck, M., Vansteenkiste, D., Steppe, K., & Ceulemans, R. (2008). ANAFORE: A stand-scale process-based forest model that includes wood tissue development and labile carbon storage in trees. Ecological Modelling, 215(4), 345–368. https://doi.org/10.1016/j.ecolmodel.2008.04.007

Dendy, F. E., & Bolton, G. C. (1976). Sediment yield-runoff drainage area relationships in the United States. Journal of Soil and Water Conservation, 31, 264–266.

Dendy, F.E., Bolton, G.C., (1976). Sediment yield-runoff drainage area relationships in the United States. Journal of Soil and Water Conservation, 31, 264−266.

Dennison, P.E., Brewer, S.C., Arnold, J.D., M.A. Moritz, M.A. Large wildfire trends in the western United States, 1984–2011. In Geophys Res. Lett., 2014, 41(8):2928-2933.

Desmet, P., Govers, G., (1996). A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. J. Soil Water Conserv. 51 (5), 427–433.

Dharumarajan, S, Bishop, TFA, Hegde, R, Singh, SK. Desertification vulnerability index—an effective approach to assess desertification processes: A case study in Anantapur District, Andhra Pradesh, India. Land Degrad Dev. 2018;29: 150–161. https://doi.org/10.1002/ldr.2850.

Diéguez - Aranda, U., Rojo, A., Castedo, F., Álvarez, J., Barrio, M., Crecente, F., González, J., Pérez, C. 2009. Herramientas selvícolas para la gestión forestal sostenible en Galicia C. d. M. R. Dirección Xeral de Montes, Xunta de Galicia (Ed.). p. 272.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs, Numerische Mathematik, 1(1), 269–271

Dimitrakopoulos, AP (2001a). Thermogravimetric Analysis of Mediterranean Plant Species. Journal of Analytical and Applied Pyrolysis, 60 (2): 123-130.

Dimitrakopoulos, AP (2001b). A Statistical Classification of Mediterranean Species Based on their Flammability Components. International Journal of Wildland Fire, 10 (2): 113-118.

Dimitrakopoulos, AP (2002). Mediterranean Fuel Models and Potential Fire Behavior in Greece. International Journal of Wildland Fire, 11 (2): 127-130.

Dimitrakopoulos, AP and Dritsa, S. (2003). Novel Nomographs for Fire Behavior Prediction in Mediterranean and Submediterranean Vegetation Types. Forestry, 76 (5): 479-490.

Dimitrakopoulos, AP and Panov, PI. (2001). Pyric Properties of Some Dominant Mediterranean Vegetation Species. International Journal of Wildland Fire, 10 (1): 23-27.

Dimitrakopoulos, AP and Papaioannou, KK (2001). Flammability Assessment of Mediterranean Forest Fuels. Fire Technology, 37 (2): 143-152.

Dimopoulou, M., Giannikos, I. Spatial Optimization of Resources Deployment for Forest-Fire Management. In Int. Trans. Oper. Res., 2001, 8:523–534.

Dong X, Li-min D, Guo-fan S, Lei T, Hui W (2005) Forest fire risk zone mapping from satellite images and GIS for Baihe Forestry Bureau, Jilin, China. *J For Res* 16(3):169–174.

Donovan, G.H., Rideout, D.B. An integer programming model to optimize resource allocation for wildfire containment. In For. Sci., 2003, 49:331–335.

Doran, J. W., & Parkin, T. B. (1994). Defining and assessing soil quality. In J.W. Doran, D.C. Coleman, D.F. Bezdicek, & B.A. Stewart (Eds.), *Defining soil quality for a sustainable environment* (Vol. 35, pp. 1–21). SSSA Special Publication, Soil Science Society of America and American Society of Agronomy.

dos Santos, J.C., Lyra, G.B., Abreu, M.C. et al. Aridity indices to assess desertification susceptibility: a methodological approach using gridded climate data and cartographic modeling. Nat Hazards 111, 2531–2558 (2022). https://doi.org/10.1007/s11069-021-05147-0.

Dragan, M., Sahsuvaroglu, T., Gitas, I. and Feoli, E. (2005), "Application and validation of a desertification risk index using data for Lebanon", Management of Environmental Quality, Vol. 16 No. 4, pp. 309-326. https://doi.org/10.1108/14777830510601190.

Duelli, P., Obrist, M.K. Biodiversity indicators: The choice of values and measures. In Agric. Ecosyst. Environ. 2003, 98:87–98.

Duff, TJ., Cawson JG., Brett C., Nyman P., Sheridan GJ., Tolhurst KG. (2018). Conditional Performance Evaluation: Using Wildfire Observations for Systematic Fire Simulator Development. *Forests*. 2018; 9(4):189. https://doi.org/10.3390/f9040189

Dufrêne, E., Davi, H., François, C., Maire, G. le, Dantec, V. L., & Granier, A. (2005). Modelling carbon and water cycles in a beech forest: Part I: Model description and uncertainty analysis on modelled NEE. Ecological Modelling, 185(2), 407–436. https://doi.org/10.1016/j.ecolmodel.2005.01.004

Duncan BW, Adrian FW, Stolen ED (2010) Isolating the lightning ignition regime from a contemporary background fire regime in east-central Florida, USA. Can J For Res 40:286–297.

Dupuy, J.-L., Pimont, F. et al. FIRETEC evaluation against the FireFlux experiment: preliminary results. In Adv. For. FireRes. Proc. from the 7th Int. Conf. For. Fire Res., University of Coimbra: Coimbra, Portugal, 2014, pp. 261–274.

Dušek, R., & Popelková, R. (2012). Theoreticalview of the shannon index in the evaluation oflandscapediversity. *Acta Universitatis Carolinae, Geographica*, *47*(2), 5–13. https://doi.org/10.14712/23361980.2015.12

Eerikäinen K (2002) A site dependent simultaneous growth projection model for *Pinus kesiya* plantations in Zambia and Zimbabwe. *For Sci* 48: 518–529.

Effinger, (2021) https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/preliminary-investigations/pi-0278-a11y.pdf

Eid, T., Hobbelstad, K. AVVIRK-2000: A Large-scale Forestry Scenario Model for Long-term Investment, Income and Harvest Analyses. In Scand. J. For. Res., 2000, 15:472-482.

Enrico Ronchi, (2021). Developing and validating evacuation models for fire safety engineering, Fire Safety Journal, Volume 120, 103020, ISSN 0379-7112, https://doi.org/10.1016/j.firesaf.2020.103020 (https://www.sciencedirect.com/science/article/pii/S0379711220300679)

ESRI. 2006. GIS Technology and Applications for the Fire Service. Available online: https://www.esri.com/content/dam/esrisites/sitecore-archive/Files/Pdfs/library/whitepapers/pdfs/fire-service-gis-applications.pdf. (Access: 14.05.2022)

ESRI. 2023. Introduction to ArcGIS Pro. Available online: https://pro.arcgis.com/en/pro-app/latest/get-started/get-started.htm. (Access 25.09.2023)

Eugenio FC, dos Santos AR, Fiedler NC, Ribeiro GA, da Silva AG, dos Santos ÁB, Paneto GG, Schettino VR. (2016). Applying GIS to develop a model for forest fire risk: a case study in Espírito Santo Brazil. *J Environ Manag* 173:65–71.

European Centre for Medium-Range Weather Forecasts (2023). Copernicus Atmosphere Monitoring Service. https://atmosphere.copernicus.eu

European Centre for Medium-Range Weather Forecasts (2023). Global Fire Assimilation System. https://confluence.ecmwf.int/pages/viewpage.action?pageId=158643360

European Environment Agency (2023). European Air Quality Index. https://airindex.eea.europa.eu/Map/AQI/Viewer/

Ewald, K.C. The neglect of aesthetics in landscape planning in Switzerland. In Land Urban Plan., 2001, 54:255-266. doi: 10.1016/S0169-2046(01)00140-2.

Fabrika, M. Simulátor biodynamiky lesa SIBYLA, koncepcia, konštrukcia a programové riešenie / SIBYLA forest biodynamics simulator, concept, design and software solution. Habilitačná práca, Zvolen: Technická univerzita vo Zvolene, 2007, p. 328. (In Slovak)

Fabrika, M., Ďurský, J. Algorithms and software solution of thinning models for SIBYLA growth simulator. In J For Sci, 2005, 51:431-445. doi: 10.17221/4577-JFS

Fabrika, M., Vaculčiak, T, 2009. Modeling Natural Disturbances in Tree Growth Model SIBYLA. In Bioclimatology and Natural Hazards, Střelcová, K., Matyas, C., Kleidon, A., et al. (eds). Springer, 2009, 155-164. doi: 10.1007/978-1-4020-8876-6_14.

Fang Z, Bailey RL, Shiver BD (2001) A multivariate simultaneous prediction system for stand growth and yield with fixed and random effects. *For Sci* 47: 550–562.

Fayyad, U., Piatetsky-Shapiro, G., Smyth, P. From Data Mining to Knowledge Discovery in Databases. In AI Magazine, 1996, 17(3):37-54.

Feltman JA, Straka TJ, Post CJ, Sperry SL (2012) Geospatial analysis application to forecast wildfire occurrences in South Carolina. *Forests* 3:265–282.

Fernandes, P.M., Pacheco, A.P., Almeida, R., Claro, J. The role of fire-suppression force in limiting the spread of extremely large forest fires in Portugal. In Eur. J. For. Res., 2016, 135:253–262.

Fernandes, PM and Botelho, HS (2003). A Review of Prescribed Burning Effectiveness in Fire Hazard Reduction. International Journal of Wildland Fire, 12 (2): 117-128.

Fernández-Alonso, J.M., Alberdi I, Álvarez-González, J.G., Vega, J.A., Canẽllas, I. and Ruiz-González, A.D. 2013. Canopy fuel characteristics in relation to crown fire potential in pine stands: analysis, modelling and classification. *Eur. J. For. Res.* 132:363–377.

Ferretti, F., Dibari, C., De Meo, I., Cantiani, P., Bianchi, M. ProgettoBosco, a Data-Driven Decision Support System for forest planning. In Mathematical and Computational Forestry & Natural-Resource Sciences (MCFNS), 2011, 3(1):27–35.

Ferro, V., & Porto, P. (2000). Sediment Delivery Distributed (SEDD) Model. Journal of Hydrologic Engineering, 5(4), 411–422. https://doi.org/10.1061/(ASCE)1084-0699(2000)5:4(411)

Finney, M. FARSITE: Fire Area Simulator-Model Development and Evaluation; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Ogden, UT, USA, 1998.

Finney, M.A. An overview of FlamMap fire modeling capabilities. Paper presented at the Fuels management—how to measure success: conference proceedings, 28-30 March 2006; Portland, OR.

Finney, M.A. Design of regular landscape level fuel treatment patterns for modifying fire growth and behavior. In For. Sci., 2001, 47(2):219-228.

Finney, M.A. FARSITE: Fire Area Simulator–model development and evaluation. Research Paper RMRS-RP-4 Revised. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 1998, 47 p.

Finney, M.A. Fire growth using minimum travel time methods. In Can. J. For. Res., 2002, 32(8):1420-1424.

Finney, M.A. FlamMap. Odgen, UT: USDA For. Serv. Rochy Mountain Research. Missoula Fire Lab., 1999.

Finney, M.A. Landscape fire simulation and fuel treatment optimization. In: Hayes, J. L.; Ager, A. A.; Barbour, J. R., tech. ed. Methods for integrating modeling of landscape change: Interior Northwest Landscape Analysis System. General Technical Report PNW-GTR-610. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Station, 2004, p. 117-131.

Finney, M.A. The challenge of quantitative risk analysis for wildland fire. In Forest Ecology & Management, 2005, 211: 97-108.

Finney, M.A., Andrews, P.L. Application and status of the FARSITE fire area simulator. Pages 755-760 in: Proceedings of the III International Conference on Forest Fire Research and 14th Conference on Fire and Forest Meteorology, Luso, Coimbra-Portugal, 16-20 November 1998, Volume I.

Finney, Mark A. 1998. FARSITE: Fire Area Simulator—Model development and evaluation. Res. Pap. RMRS-RP-4. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 47 p.

Finney, Mark A. 2006. An overview of FlamMap fire modeling capabilities. In: Andrews, Patricia L.; Butler, Bret W., comps. 2006. Fuels management—How to measure success: Conference Proceedings. 2006 March 28–30; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: 213–220.

Fire and Environmental Research Applications Team (2023). Fuel and Fire Tools (FFT).

FIRE.ORG. 2022. What's New in FARSITE 4.0. Available online: http://fire.org/downloads/farsite/WebHelp/referenceguide/what_s_new_in_farsite4.htm. (Accessed 18.08.2023)

FIREGROWTHMODEL.CA. 2022. Prometheus. Available online: https://firegrowthmodel.ca/pages/prometheus_overview_e.html. (Access 14.11.2022)

FIREGROWTHMODEL.CA. 2023. Burn-P3. Available online: https://firegrowthmodel.ca/pages/burnp3_overview_e.html. (Access 22.09.2023)

FIRELAB.ORG. 2022. FOFEM/SpatialFOFEM - fire effects model. Available online: https://www.firelab.org/project/fofem-fire-effects-model. (Accessed 17.07.2022)

Fischer, A.P. Forest landscapes as social-ecological systems and implications for management. In Land Urban Plan., 2018, 177:138-147. doi: 10.1016/j.landurbplan.2018.05.001.

Fischer, A.P., Klooster, A., Cirhigiri, L. Cross-boundary cooperation for landscape management: collective action and social exchange among individual private forest landowners. In Land Urban Plan., 2019, 188:151-162. doi: 10.1016/j.landurbplan.2018.02.004.

Flare Wildfire Research. 2023. Software: FROST family. Available online: https://www.flarewildfire.com/software/frost-family/. (Access 25.06.2023)

Flare Wildfire Research. 2023. Software: PHOENIX Rapidfire. Available online: https://www.flarewildfire.com/software/phoenix-rapidfire/. (Access 25.06.2023)

FLARE Wildfire Research. 2023. Software: The Landscape Decision Support System (DSS). Available online: https://www.flarewildfire.com/software/decision-support-system/. (Access 21.07.2023)

FOREST EUROPE. State of Europe’s Forests. 2015. Available online: http://www.foresteurope.org/docs/fullsoef2015.pdf. (Access 19.09.2023).

Forest Research. 2023. Tools and Resources: ForestGALES. Available online: https://www.forestresearch.gov.uk/tools-and-resources/fthr/forestgales/. (Access: 17.08.2023)

Forrester, D. I., & Tang, X. (2016). Analysing the spatial and temporal dynamics of species interactions in mixed-species forests and the effects of stand density using the 3-PG model. Ecological Modelling, 319, 233–254. https://doi.org/10.1016/j.ecolmodel.2015.07.010

Foster, G. R, and L. J. Lane, (1987). User requirements: USDA Water Erosion Prediction Project (WEPP). NSERL Report No. 1. West Lafayette, Ind.: USDA-ARS National Soil Erosion Research Laboratory.

Foster, G.R., Meyer, L.D., Onstad, C.A., (1977). An Erosion Equation Derived from Basic Erosion Principles. Transactions of the ASAE. 20 (4): 0678-0682. (doi: 10.13031/2013.35627).

Frandsen, William H. 1971. Fire spread through porous fuels from the conservation of energy. Combustion and Flame 16(1): 9–16.

Frank, S., Fürst, Ch., Koschke, L., Makeschin, F. A contribution towards a transfer of the ecosystem service concept to landscape planning using landscape metrics. In Ecological Indicators, 2012, 10:30-38.

Fried, JS, Winter, GJ, Gilless, JK (2000). Assessing the Benefits of Reducing Fire Risk in the Wildland-Urban Interface: A Contingent Valuation Approach. International Journal of Wildland Fire, 9 (1): 9 - 20

Fulton, S., West, B. Forestry impacts on water quality. Chapter 21. In: Wear, David N.; Greis, John G., eds. Southern forest resource assessment. Gen. Tech. Rep. SRS-53. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station, 2002, 635 p.

Galeso M. (2016) Waze: An Easy Guide to the Best Features. 1st ed. North Charleston, SC, USA: CreateSpace Independent Publishing Platform. https://www.waze.com/waze

Gallego Arrubla, J.A., Ntaimo, L., Stripling, C. Wildfire initial response planning using probabilistically constrained stochastic integer programming. In Int. J. Wildland Fire, 2014, 23:825–838.

Gardner, T.A., Barlow, J., Chazdon, R., Ewers, R.M., Harvey, C.A., Peres, C.A., Sodhi, N.S. Prospects for tropical forest biodiversity in a human-modified world. In Ecol. Lett., 2009, 12:561–582.

Gavrilovic, S., (1962). A method for estimating the average annual quantity of sediments according to the potency of erosion. Bulletin of the Faculty of Forestry, 26, 151−168. (in Serbian)

Gavrilovic, S., (1970). Modern ways of calculating the torrential sediment and erosion mapping. In: Erosion, Torrents, and Alluvial Deposits Proceedings. Belgrade, Serbia: Yugoslav Committee for International Hydrological decade, 1, 85–100. (in Serbian)

Gavrilovic, S., (1972). Engineering of torrents and erosion. Journal of Construction (Special Issue). Belgrade: Izgradnja. (in Serbian)

Gavrilovic, Z. (1988). Use of an Empirical Method Erosion Potential Method for Calculating Sediment Production and Transportation in Unstudied or Torrential Streams. International Conference on River Regime. Hydraulics Research Limited, Wallingford, Oxon UK. 411-422.

Gbondo-Tugbawa, S.S., C.T. Driscoll, J.D. Aber, and G.E. Likens. (2001). The evaluation of an integrated biogeochemical model (PnET-BGC) at a northern hardwood forest ecosystem. Water Resources Research, 37:1057-1070.

Genton MG, Butry DT, Gumpertz ML, Prestemon JP (2006) Spatio-temporal analysis of wildfire ignitions in the St Johns River Water Management District, Florida. Int J Wildland Fire 15:87–97.

Gibbons, P., Lindenmayer, DB, Barry, SC, Tanton, MT (2000). The Effects of Burning Slash on Mortality and Collapse of Retained Trees on Logged Sites in South-Eastern Australia. Forest Ecology and Management, 139 (1-3): 51-61.

Gilani, H., Ahmad, A., Younes, I., and Abbas, S. (2022). Impact assessment of land cover and land use changes on soil erosion changes (2005–2015) in Pakistan. Land Degrad. Dev. 33, 204–217. doi: 10.1002/ldr.4138

Gilliams, S., Van Orshoven, J., Muys, B., Kros, H., Heil, G.W., Van Deursen, W. AFFOREST sDSS: a metamodel based spatial decision support system for afforestation of agricultural land. In New Forests, 2005, 30:33–53.

Giordano, A., Bonfils, P., Briggs, D.J., de Sequeira, E.M., de Laburu, C.R., Yassoglou, N. (1991). The methodological approach to soil erosion and important land resources evaluation of the European Community. Soil Technol., 4 (1991), pp. 65-77.

Glasa, J., Weisenpacher, P., Halada, L. Analysis of Forest Fire Behaviour by Advanced Computer Fire Simulators. In Communications - Scientific Letters of the University of Zilina 2011, 13(2):26-31. doi:10.26552/com.C.2011.2.26-31.

Goldereich, O. P, NP, and NP-Completeness: The Basics of Computational Complexity, Cambridge University Press: Cambridge, UK, 2010, Chapter 4.

Gómez-Vázquez, I., Crecente-Campo, F., Diéguez-Aranda, U. and Castedo-Dorado, F. 2013. Modelling canopy fuel variables in *Pinus pinaster* Ait. and *Pinus radiata* D. Don stands in northwestern Spain. *Ann. For. Sci.* 70:161–172.

Gonzales, A., Chase, J.M., O'Connor, M.I. A framework for the detection and attribution of biodiversity change. In Phil. Trans. R. Soc., 2023, B378:0220182. doi: 10.1098/rstb.2022.0182.

Goodrich, D.C., Sheppard, S., Barlow, J., Korgaonkar, Y., Guertin, P., Unkrich, C., & Burns, S. (2011). The Automated Geospatial Watershed Assessment (AGWA) Tool for Rapid Post-Fire Watershed Assessments. AGWA Overview presentation: NERL Eco Modeling Mtg._Las Vegas, March 2011.

Goodrich, D.C., UnKrich, C.L., Smith, R.E., Guertin, D.P., Hernandez, M., Burns, I.S., Massart, J.E., Levick, L., Miller, S.N., Semmens, D.J., & Kepner, W.G. (2011). The AGWA-KINEROS2 suite of modeling tools. Watershedmanagement 2010.ASCE2011:, 1294-1305.

Goodrick, S. L., Achtemeier, G. L., Larkin, N. K., Liu, Y., & Strand, T. M. (2012). Modelling smoke transport from wildland fires: a review. International Journal of Wildland Fire, 22(1), 83-94.

Gotelli, N. and Colwell, R. (2001). Quantifying biodiversity: procedures and pitfalls in the measurement and comparison of species richness. Ecology Letters, 4(4), 379-391. https://doi.org/10.1046/j.1461-0248.2001.00230.x

Govers, G., Poesen, J., (1988). Assessment of the interrill and rill contributions to total soil loss from an upland field plot. Geomorphology 1 (4), 343–354.

Gracia, C. A., Tello, E., Sabaté, S., & Bellot, J. (1999). GOTILWA: An Integrated Model of Water Dynamics and Forest Growth. In F. Rodà, J. Retana, C. A. Gracia, & J. Bellot (Eds.), Ecology of Mediterranean Evergreen Oak Forests (pp. 163–179). Springer.

Graham, RT, Harvey, EA, Jain, TB, Tonn, JR (1999). The Effects of Thinning and Similar Stand Treatments on Fire Behavior in Western Forests . General Techical Report PNW-GTR-463, USDA Forest Service Pacific Northwest Research Station.

Granda, B., León, J., Vitoriano, B., Hearne, J. Decision Support Models and Methodologies for Fire Suppression. In Fire, 2023, 6:37. https://doi.org/10.3390/fire6020037

Grant, R. F., Jarvis, P. G., Massheder, J. M., Hale, S. E., Moncrieff, J. B., Rayment, M., Scott, S. L., & Berry, J. A. (2001). Controls on carbon and energy exchange by a black spruce–moss ecosystem: Testing the mathematical model Ecosys with data from the BOREAS Experiment. Global Biogeochemical Cycles, 15(1), 129–147.

Griffith, D., Still, C., & Kim, Y. (2018). An R implementation of the 3PG (physiological principles predicting growth) model (version 0.1.0). Retrieved from https://github.com/griffithdan/r3PG

Guishan Cui , Woo-Kyun Lee leewk@korea.ac.kr , Doo-Ahn Kwak , Sungho Choi , Taejin Park & Jongyeol Lee (2011) Desertification monitoring by LANDSAT TM satellite imagery, Forest Science and Technology, 7:3, 110-116, DOI: 10.1080/21580103.2011.594607.

Guo F, Su Z, Wang G, Sun L, Lin F, Liu A (2016) Wildfire ignition in the forests of southeast China: identifying drivers and spatial distribution to predict wildfire likelihood. Appl Geogr 66:12–21.

Haight, R.G., Fried, J.S. Deploying wildland fire suppression resources with a scenario-based standard response model. In INFOR Inf. Syst. Oper. Res., 2007, 45:31–39.

Hajigholizadeh, M., Melesse, A.M. and Fuentes, H.R. (2018). Erosion and Sediment Transport Modelling in Shallow Waters: A Review on Approaches, Models and Applications. Int. J. Environ. Res. Public Health 2018, 15, 518; doi:10.3390/ijerph15030518.

Hakanson, L. (1980). An ecological risk index for aquatic pollution control.a sedimentological approach. *Water Research*, *14*(8), 975–1001. https://doi.org/10.1016/0043-1354(80)90143-8

Haklay, M., & Weber, P. (2008). Openstreetmap: User-generated street maps. IEEE Pervasive computing, 7(4), 12-18. https://wiki.openstreetmap.org/wiki/Main_Page

Han, J., Kamber, M., Pei, J. Data Mining: Concepts and Techniques. 3rd Edition, Morgan Kaufmann Publishers, Burlington, 2011, 703 pp. ISBN 978-0-12-381479-1.

Hao QY, Meng FR, Zhou YP, Wang JX (2005) A transition matrix growth model for uneven-aged mixed-species forests in the Changbai Mountains, northern China. *New For* 29:221–231.

Hart P. E., Nilsson N. J., Raphael B. (1968), A Formal Basis for the Heuristic Determination of Minimum Cost Paths, IEEE transactions on Systems Science and Cybernetics 4.2 (1968): 100-107.

Hartnell, B. Firefighter! An application of domination. In Proceedings of the the 25th Manitoba Conference on Combinatorial Mathematics and Computing, University of Minitoba, Winnipeg, MB, Cadada, 1–3 October 1995.

Hastie, T., Tibshirani, R., Friedman, J. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Series in Statistics, 2009, 767 p. ISBN 978-0387848570.

Hastings, W.K. Monte Carlo sampling methods using Markov chains and their applications. In Biometrika, 1970, 57(1):97–109. doi:10.1093/biomet/57.1.97. ISSN 0006-3444. S2CID 21204149.

Hennes, L.C., Irving, M.J., Navon, D. Forest Control and regulation: a Comparison of Traditional Methods and alternatives U.S. Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station, Berkeley, CA. Res. Note PSW-RN-23111, 1971, 10 p.

Hill, D., Fashmam, M., Shaw, P. Handbook of Biodiversity methods: Survey, Evaluation and Monitoring. Cambridge University Press, Cambridge, 2005, 588 p.

Hof, J., Omi, P.N., Bevers, M., Laven, R.D. A Timing-Oriented Approach to Spatial Allocation of Fire Management Effort. In For. Sci., 2000, 46:442–451.

Homchaudhuri, B., Kumar, M., Cohen, K. Genetic algorithm based simulation-optimization for fighting wildfires. In Int. J. Comput. Methods, 2013, 10:1350035.

Hood, S.M., McHugh, C., Ryan, K.C., Reinhardt, E., Smith, S. Evaluation of a post-fire tree mortality model for western US conifers. In International Journal of Wildland Fire, 2007,16:679–689.

Hooke, R., Jeeves, T.A. “Direct search” solution of numerical and statistical problems. In J Assoc Comput Mach, 1961, 8:212–229.

Hool, J.N. A dynamic programming - Markov chain approach to forest production control. Forest Science, 1966, 12(suppl_3):a0001–z0001.

Howson, C. The Logic of Bayesian Probability. In Corfield, D.; Williamson, J. (eds.). Foundations of Bayesianism. Dordrecht: Kluwer, 2001, pp. 137–159. ISBN 1-4020-0223-8.

Hu, B., Windbichler, A., Raidl, G.R. A New Solution Representation for the Firefighter Problem. In Proceedings of the European Conference on Evolutionary Computation in Combinatorial Optimization, Copenhagen, Denmark, 8–10 April 2015, Springer: Berlin/Heidelberg, Germany, 2015, pp. 25–35.

Hu, X., Ntaimo, L. Integrated simulation and optimization for wildfire containment. In ACM Trans. Model. Comput. Simul., 2009, 19:1–29.

Hughes, A.O., Quinn, J.M. The effect of forestry management activities on stream water quality within a headwater plantation Pinus radiata forest. In For. Ecol. Manag., 2019, 439:41–54. doi:10.1016/j.foreco.2019.02.035.

Huxley, J.S. and Teissier, G. 1936. Terminology of relative growth. *Nature* 137: 780–781.

Hysa A, Başkaya FAT (2018) A GIS based method for indexing the broad-leaved forest surfaces by their wildfire ignition probability and wildfire spreading capacity. Model Earth Syst Environ 5:71-84.

Igwe P.U., Onuigbo A.A., Chinedu O. C., Ezeaku I.I., Muoneke M.M., (2017). Soil Erosion: A Review of Models and Applications. International Journal of Advanced Engineering Research and Science (IJAERS), 4, (12), 138-150.

Inengite, A., Abasi, C., & Walter, C. (2015). Application of Pollution Indices for the Assessment of Heavy Metal Pollution in Flood Impacted Soil. *International Research Journal of Pure and Applied Chemistry*, *8*(3), 175–189. https://doi.org/10.9734/IRJPAC/2015/17859

Ingalsbee, T., Raja, U. The rising costs of wildfire suppression and the case for ecological fire use. In The Ecological Importance of Mixed-Severity Fires; Elsevier: Amsterdam, The Netherlands, 2015, pp. 348–371.

Intharathirat, R., Abdul Salam, P., Kumar, S., Untong, A. Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. In Waste Management, 2015, 39: 3–14.

Jaafari A, Pourghasemi HR (2019) Factors Influencing Regional-Scale Wildfire Probability in Iran: An Application of Random Forest and Support Vector Machine. In Spatial Modeling in GIS and R for Earth and Environmental Sciences (pp. 607–619). Elsevier.

Jahani, A. Forest landscape aesthetic quality model (FLAQM): A comparative study on landscape modelling using regression analysis and artificial neural networks. In Journal of Forest Science, 2019, 65(2):61–69. doi: 10.17221/86/2018-JFS.

Jaiswal RK, Mukherjee S, Raju KD, Saxena R (2002) Forest fire risk zone mapping from satellite imagery and GIS. *Int J Appl Earth Obs Geoinf* 4:1–10.

Jakeman, A.J. and Hornberger, G.M., (1993). How much complexity is warranted in a rainfall-runoff model? Water Resour. Res., 29: 2637-2649.

Jetten, V., Govers, G. and Hessel, R. (2003). Erosion models: quality and spatial predictions. Hydrological. Processes, 17: 887-900.

Jiménez, E., Vega, J.A., Fernández-Alonso, J.M., Vega-Nieva, D., Álvarez-Gonzalez, J.G. and Ruiz-González, A.D. 2013. Allometric equations for estimating canopy fuel load and distribution of pole-size maritime pine trees in five Iberian provenances. *Can. J. Forest Res.* 43: 149–158.

Johnson, A., Woodard, P. and Titus, S. 1989. Lodgepole pine and white spruce fuel weights predicted from height and crown width. *Can. J. For. Res.* 19: 527–530.

Johnson, K.N., Scheurman, H.L.. Techniques for prescribing optimal timber harvest and investment under different objectives - discussion and synthesis. In For. Sci., 1977, 18:1-31. doi: 10.1093/forestscience/23.s1.a0001

Johnston, P., Kelso, J., Milne, G. Efficient simulation of wildfire spread on an irregular grid. In Int. J. Wildland Fire, 2008, 17: 614.

Jonsson, B., Jacobsson, J., Kallur, H. (1993): The Forest Management Planning Package. Theory and application. In Studia Forestalia Suecica, 1993, 189:56.

Judea, P. Heuristics: Intelligent Search Strategies for Computer Problem Solving. New York, NY: Addison-Wesley, 1983, p. vii.

Jung, S., Rasmussen, L.V., Watkins, C., Newton, P., Agrawal, A. Brazil's national environmental registry of rural properties: implications for livelihoods. In Ecol. Econ., 2017, 136:53-61. doi: 10.1016/j.ecolecon.2017.02.004.

Kalabokidis, K., Roussou, O., Vasilakos, C., Markopoulou, D. Spatial modeling of landscape fire fuels and behavior. In Proceedings 7th Pan-Hellenic Geographical Conference of the Hellenic Geographical Society, 14-17 Oct. 2004, vol. I. Dept. of Geography, Univ. of the Aegean, Mytilene, pp. 486-494.

Kalabokidis, KD and Omi, PN (1998). Reduction of Fire Hazard through Thinning / Residue Disposal in the Urban Interface. International Journal of Wildland Fire, 8 (1): 29-35.

Kaloudis S, Tocatlidou A, Lorentzos NA, Sideridis AB, Karteris M (2005) Assessing wildfire destruction danger: a decision support system incorporating uncertainty. *Ecol Model* 181:25–38.

Kaloudis, S., 2008. Decision support system for the management of forest ecosystems based on geographic information systems and in knowledge systems. PhD dissertation, Agricultural University Athens, p. 210.

Kaloudis, S., Karteris, M., Lorentzos, N., Sideridis, A. (2001). Conceptual Framework of a Decision Support System for the Management of Lowland Pine Forests Aiming at Reducing Wildfire Damages . In: International Conference on Forest Research: A Challenge for an Integrated European Approach (Radoglou, K., ed.), Pp. 287–292, Thessaloniki, Greece.

Kamilaris, A., Filippi, J. B., Padubidri, C., Koole, R., & Karatsiolis, S. (2023). Examining the potential of mobile applications to assist people to escape wildfires in real-time. *Fire Safety Journal*, *136*, 103747. https://github.com/rise-centre/Escape-Wildfires

Kandel, D.D.; Western, A.W.; Grayson, R.B.; Turral, H.N. Process parameterization and temporal scaling in surface runoff and erosion modelling. Hydrol. Process. 2004, 18, 1423–1446.

Kanga S, Sharma L K, Pandey PC, Nathawat MS (2014) GIS Modelling approach for forest fire risk assessment and management. *Int J Adv Remote Sens GIS Geogr* 2:30–44.

Kangas, A., Kangas, J., Kurttila, M. Decision support for forest management. Managing Forest Ecosystems 16. Springer, 208, 222 p.

Kanito, D. and Feyissa, S. (2021). Comparison and Applicability of Selected Soil Erosion Estimation Models. Hydrology, 9(4): 79–87. DOI: 10.11648/j.hyd.20210904.12

Kapusniak, J., Majlingova, A. Posudzovanie vhodnosti nasadenia hasičskej techniky určenej na hasenie lesných požiarov v podmienkach SR / Assessing the suitability of deployment of firefighting equipment for extinguishing forest fires in the conditions of the Slovak Republic. In Manažment rizík požiarov v prírodnom prostredí: zborník vedeckých prác / ed. Andrea Majlingová, Boris Toman ; rec. Anton Osvald ... [et al.]. - Bratislava: Požiarnotechnický a expertízny ústav MV SR, 2015, p. 53-61. ISBN 978-80-89051-18-2.

Karydas C.G , Panagos , P. (2016). Modelling monthly soil losses and sediment yields in Cyprus. Int. J. Digit. Earth. 9 (8), 766–78.

Karydas, C.G., Panagos, P., Gitas, I.Z. (2014). A classification of water erosion models according to their geospatial characteristics. Int. J. Digit. Earth, 7 (3) (2014), pp. 229-250

Katuwal, H., Dunn, C.J., Calkin, D.E. Characterising resource use and potential inefficiencies during large-fire suppression in the western US. In Int. J. Wildland Fire, 2017, 26:604–614.

Kavian A, Hoseinpoor SS, Solaimani K, Jafari B. (2017). Simulating the effects of land-use changes on soil erosion using the RUSLE model. Geocarto Int. 32(1):97–111

Kellomäki, S., & Väisänen, H. (1997). Modelling the dynamics of the forest ecosystem for climate change studies in the boreal conditions. Ecological Modelling, 97(1), 121–140. https://doi.org/10.1016/S0304-3800(96)00081-6

Kempf, M.: Monitoring landcover change and desertification processes in northern China and Mongolia using historical written sources and vegetation indices, Clim. Past Discuss. [preprint], https://doi.org/10.5194/cp-2021-5, 2021.

Khalil, U., and Aslam, B. (2022). Geospatial-based soil management analysis using novel technique for better soil conservation. Model. Earth Syst. Environ. 8, 259–275. doi: 10.1007/s40808-020-01078-0

Khanamani, A., Fathizad, H., Karimi, H. et al. Assessing desertification by using soil indices. Arab J Geosci 10, 287 (2017). https://doi.org/10.1007/s12517-017-3054-5.

Khanina, L., Bobrovsky, M., Komarov, A., Mikhajlov, A., Modelling dynamics of forest ground vegetation diversity under different forest management regimes. In For. Ecol. Manage., 2007, 248: 80-94.

Kirschbaum, M. U. F. (1999). Modelling forest growth and carbon storage in response to increasing CO2 and temperature. Tellus B, 51(5), 871–888.

Knapp, EE, Keeley, JE, Ballenger, EA, Brennan, TJ (2005). Fuel Reduction and Coarse Woody Debris Dynamics with Early Season and Late Season Prescribed Fire in a Sierra Nevada Mixed Conifer Forest. Forest Ecology and Management, 208 (1-3): 383-397.

Knight, I.K., Sullivan, A.L. A semi-transparent model of bushfire flames to predict radiant heat flux. In International Journal of Wildland Fire, 2004, 13:201–207. doi:10.1071/WF03047.

Knisel, W.G.; Nicks, A.D. *CREAMS: A Field Scale Model for Chemicals, Runoff, and Erosion from Agriculture Management System*, 26th ed.; Dept. of Agriculture, Science and Education Administration: Corvallis, OR, USA, 1981; Volume 1.

Komarov, A., Chertov, O., Zudin, S., Nadporozhskaya, M., Mikhailov, A., Bykhovets, S., Zudina, E., Zoubkova. EFIMOD 2 -- A model of growth and elements cycling in boreal forest ecosystems. In Ecological Modelling, 2003, 170(2-3):373-392.

Komarov, A.S., Chertov, O.G., Mikhailov, and Autors’ Collective (14 names). Modelling Dynamics of Organic Matter in Forest Ecosystems [Responsible editor V.N. Kudeyarov]. Nauka, Moscow. 2007, 380 p.

Könnyű, N., Tóth, S.F. A cutting plane method for solving harvest scheduling models with area restrictions. In Eur. J. Oper. Res., 2013, 228:236-248. doi: 10.1016/j.ejor.2013.01.020.

Könnyű, N., Toth, S.F., McDill, M.E., Rajasekaran, B. Temporal connectivity of mature patches in forest planning models. In For. Sci., 2015, 60:1089-1099. doi: 10.5849/forsci.12-112

Kosmas, C.; Ferrara, A.; Briassoulis, H.; Imeson, A. Methodology for mapping Environmentally Sensitive Areas (ESAs) to Desertification. In The Medalus Project Mediterranean Desertification and Land Use. Manual on Key Indicators of Desertification and Mapping Environmentally Sensitive Areas to Desertification; Kosmas, C., Kirkby, M., Geeson, N., Eds.; European Union: Brussels, Belgium, 1999.

Kosmas, C.; Kirkby, M.; Geeson, N. The MEDALUS Project. Mediterranean Desertification and Land Use. Manual on Key Indicators of Desertification and Mapping Environmentally Sensitive Areas to Desertification; European Union: Brussels, Belgium, 1999.

Kourkouta L. et al (2021). Effects of Forest Fire on Health. EAS J Nurs Midwifery, 3(5), 219-222.

Koutsoyiannis, D., (2000). Broken line smoothing: a simple method for interpolating and smoothing data series, Environmental Modelling & Software, 15, 139-149.

Koutsoyiannis, D., Tarla, K., (1987). Sediment yield estimations in Greece. Technica Chronica, A-7 (3), 127−154.

Kowalska, J. B., Mazurek, R., Gąsiorek, M., & Zaleski, T. (2018). Pollution indices as useful tools for the comprehensive evaluation of the degree of soil contamination–A review. *Environmental Geochemistry and Health*, *40*(6), 2395–2420. https://doi.org/10.1007/s10653-018-0106-z

Krajicek, J.E., Brinkman, K.E. and Gingrich, S.F. 1961. Crown competition-a measure of density. *For. Sci.* 7: 35-42.

Kramer, K., Groen, T. A., & van Wieren, S. E. (2003). The interacting effects of ungulates and fire on forest dynamics: An analysis using the model FORSPACE. Forest Ecology and Management, 181(1), 205–222.

Kramer, K., Leinonen, I., Bartelink, H. H., Berbigier, P., Borghetti, M., Bernhofer, C., Cienciala, E., Dolman, A. J., Froer, O., Gracia, C. A., Granier, A., Grünwald, T., Hari, P., Jans, W., Kellomäki, S., Loustau, D., Magnani, F., Markkanen, T., Matteucci, G., … Vesala, T. (2002). Evaluation of six process-based forest growth models using eddy-covariance measurements of CO2 and H2O fluxes at six forest sites in Europe. Global Change Biology, 8(3), 213–230.

Krawchuk, M.A., Cumming, S.G., Flannigan, M.D., and Wein, R.W. 2006. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. Ecology 87:458–468.

Kroese, D.P., Brereton, T., Taimre, T., Botev, Z.I. (2014). "Why the Monte Carlo method is so important today". In WIREs Comput Stat., 2014, 6(6): 86–392. doi:10.1002/wics.1314. S2CID 18521840.

Küçük, O., Bilgili, E. and Sağlam, B. 2008. Estimating crown fuel loading for Calabrian pine and Anatolian black pine. *Int J Wildl Fire* 17:147–154.

Küçük, O., Goltas, M., Demirel, T., Mitsopoulos, I. and Bilgili, E. 2021. Predicting canopy fuel characteristics in *Pinus brutia* Ten., *Pinus nigra* Arnold and *Pinus pinaster* Ait. Forest stand variables in North-Western Turkey. *Environ. Eng. Manag. J.* 20:308-319.

Kuligowski, E. (2021). Evacuation decision-making and behavior in wildfires: Past research, current challenges and a future research agenda. *Fire Safety Journal*, *120*, 103129.

Kurttila, M. The spatial structure of forests in the optimization calculations of forest planning – a landscape ecological perspective. In For. Ecol. Manag., 2001, 142:129-142. doi: 10.1016/S0378-1127(00)00343-1.

Kwak H, Lee WK, Saborowski J, Lee SY, Won MS, Koo KS, Lee MB, Kim SN (2012) Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea. *Int J Geogr Inf Sci* 26:1589–1602.

Lagouvardos, K., V. Kotroni, A. Koussis, H. Feidas, A. Buzzi, and P. Malguzzi, 2003: The Meteorological Model BOLAM at the National Observatory of Athens: Assessment of Two-Year Operational Use. J. Appl. Meteor. Climatol., 42, 1667–1678, https://doi.org/10.1175/1520-0450(2003)042<1667:TMMBAT>2.0.CO;2.

Larkin, N. K., O'Neill, S. M., Solomon, R., Raffuse, S., Strand, T., Sullivan, D. C., ... & Ferguson, S. A. (2009). The BlueSky smoke modeling framework. International journal of wildland fire, 18(8), 906-920.

Lasch-Born, P., Suckow, F., Reyer, C. P. O., Gutsch, M., Kollas, C., Badeck, F.-W., Bugmann, H. K. M., Grote, R., Fürstenau, C., Lindner, M., & Schaber, J. (2020). Description and evaluation of the process-based forest model 4C v2.2 at four European forest sites. Geoscientific Model Development, 13(11), 5311–5343. https://doi.org/10.5194/gmd-13-5311-2020

Latham, D.J., Schlieter, J.A. Ignition probabilities of wildland fuels based on simulated lightning discharges. Ogden, UT: USDA Forest Service, Intermountain Research Station, General Technical Report INT-GTR-411, 1989.

Lavdas, L. G. (1996). Program VSMOKE—User's Manual. General Technical Report SRS-6. Asheville, NC: USDA Forest Service, Southern Research Station.

Leuschner, W.A. Forest Regulation, Harvest Scheduling, and Planning Techniques. Will Intermediat Publish, 1990, p. 304 pp.

Lexer, M.J., Vacik, H., Palmetzhofer, D. and Oitzinger, G. 2005. A decision support tool to improve forestry extension services for small private landowners in southern Austria. In Computers and Electronics in Agriculture, 2005, 49(1):81-102.

Li D., Cova TJ., Dennison P.E., (2018). Setting Widlfire Evacuation Triggers by Coupling Fire and Traffic Simulation Models: A Spatiotempral GIS Approach. Fire Technology 2018. https://content.csbs.utah.edu/~pdennison/reprints/denn/2019_Li_etal_FT.pdf

Liedloff, A.C., Coughenour, M.B., Ludwig, J.A., Dyer, R. (2001). Modelling the Trade-off between Fire and Grazing in a Tropical Savanna Landscape, Northern Australia. Environment International, 27 (2-3): 173-180.

Lin, C.H., Ferng,Y.M., Hsu, W.S. Investigating the effect of computational grid sizes on the predicted characteristics of thermal radiation for a fire. In Appl. Therm. Eng., 2009, 29(11–12): 2243–2250. doi:10.1016/j.applthermaleng.2008.11.010.

Linn, R. A Transport Model for Prediction of Wildfire Behavior; Los Alamos National Lab.: Los Alamos, NM, USA, 1997.

Linn, R., Winterkamp, J., Colman, J. J., Edminster, C., & Bailey, J. D. (2005). Modeling interactions between fire and atmosphere in discrete element fuel beds. International Journal of Wildland Fire, 14(1), 37-48.

Linn, R.; Cunningham, P. Numerical simulations of grass fires using a coupled atmosphere-fire model: Basic fire behavior and dependence on wind speed. In J. Geophys. Res. Atmos., 2005, 110: 1–19.

Linn, R.R. A transport model for prediction of wildfire behavior. In Sci. Rep. LA-13334-T, 1997, 195 pp., Los Alamos Natl. Lab., Los Alamos, N. M. doi: 10.2172/505313.ň

Linn, R.R. A transport model for prediction of wildfire behavior. In Sci. Rep. LA-13334-T, 1997, 195 pp., Los Alamos Natl. Lab., Los Alamos, N. M. doi: 10.2172/505313

Linn, R.R., Reisner, J.M., Colman, J.J., Winterkamp, J. Studying wildfire behavior using FIRETEC. In Int. J. Wildland Fire, 2002, 11: 233–246.

Liodakis, S., Bakirtzis, D., Dimitrakopoulos, AP (2003). Autoignition and Thermogravimetric Analysis of Forest Species Treated with Fire Retardants. Thermochemica Acta, 399 (1-2): 31-42.

Lischke, H., Zimmermann, N. E., Bolliger, J., Rickebusch, S., & Löffler, T. J. (2006). TreeMig: A forest-landscape model for simulating spatio-temporal patterns from stand to landscape scale. Ecological Modelling, 199(4), 409–420. https://doi.org/10.1016/j.ecolmodel.2005.11.046

Liu C, Zhang L, Davis CJ, Solomon DS, Brann TB, Caldwell LE (2003) Comparison of neural networks and statistical methods in classification of ecological habitats using FIA data. *For Sci* 49: 619–631.

Liu, J.S., Liang, F., Wong, W.H. The Multiple-Try Method and Local Optimization in Metropolis Sampling. In Journal of the American Statistical Association, 2000, 95(449):121–134. doi:10.1080/01621459.2000.10473908.

Liu, W.Y., Lin, C.C. Spatial forest resource planning using a cultural algorithm with problem-specific information. In Envir. Model. Soft., 2015, 71:126-137. doi: 10.1016/j.envsoft.2015.06.002.

Lopes, A.M.G., Cruz, M.G., Viegas, D.X. FireStation—An integrated software system for the numerical simulation of fire spread on complex topography. In Environ. Model. Softw., 2002, 17:269–285.

Lopes, A.M.G.; Cruz, M.G.; Viegas, D.X. FireStation—An integrated software system for the numerical simulation of fire spread on complex topography. Environ. Model. Softw. 2002, 17, 269–285.

Lu, X.X., Ashmore, P., and Wang, J., (2003). Sediment yield mapping in a large river basin: the Upper Yangtze, China. Environmental Modelling & Software, 18, 339–353.

Luenberger, D.G.; Ye, Y. (2008). Linear and nonlinear programming. In International Series in Operations Research & Management Science, Vol. 116 (Third ed.). New York: Springer, 2008, 546 pp. ISBN 978-0-387-74502-2

Lutes DC (2020) First Order Fire Effects Model: FOFEM 6.7, User's guide. (Fire And Aviation Management Rocky Mountain Research Station Fire Modeling Institute)

Lutes, D.C. FOFEM 6.0 user guide. Fort Collins, CO: USDA Forest Service, Rocky Mountain Research Station, 2012.

Lutes, D.C., Keane, R.E., Caratti, J.F., Key, C.H., Benson, N.C., Sutherland, S., Gangi, L.J. FIREMON: Fire effects monitoring and inventory system. Gen. Tech. Rep. RMRS-GTR-164. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2006.

Lykoudi, E., Zarris, D., (2004). The influence of drainage network formation and characteristics over a catchment's sediment yield. 2nd International Conference on Fluvial Hydraulics, Naples, Italy, 793–800, University of Napoli - Federico II, 2004.

Majlingova, A. The opening-up of forest for fire extinguishing purposes. In Croat. J. For. Eng., 2012, 33(1):159-168.

Mandel, J., Beezley, J. D., & Kochanski, A. K. (2011). Coupled atmosphere-wildland fire modeling with WRF-Fire version 3.3. Geoscientific Model Development Discussions, 4(1), 497-545.

Maranghides A and Link E (2023). WUI Fire Evacuation and Sheltering Considerations: Assessment, Planning, and Execution (ESCAPE). (National Institute of Standards and Technology, Gaithersburg, MD), NIST Technical Note (TN) 2262. https://doi.org/10.6028/NIST.TN.2262

Marques, M., Juerges, N., Bogres, J.G. 2020. Appraisal framework for actor interest and power analysis in forest management - Insights from Northern Portugal. In Fores Policy and Economics, 2020, 111. doi: 10.1016/j.forpol.2019.102049

Martell, D.L. A review of operational research studies in forest fire management. Can. J. For. Res. 1982, 12, 119–140.

Martín Y, Zúñiga-Antón M, Rodrigues Mimbrero M (2019) Modelling temporal variation of fire-occurrence towards the dynamic prediction of human wildfire ignition danger in northeast Spain Geomatics. Nat Hazards Risk 10:385–411.

Martins, T.V., Gomide, L.R., Ferraz Filho, A.C., Silva, P.R., Melo, L.A. Eucalyptus clonal mosaics in forest planning and their effects on wood production and economy. In Sci. For., 2017, 45:727-737.

Massada AB, Syphard AD, Stewart SI, Radeloff VC (2013) Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. Int J Wildland Fire 22:174–183.

Mazurek, R., Kowalska, J., Gąsiorek, M., Zadrożny, P., Józefowska, A., Zaleski, T., Kępka, W., Tymczuk, M., & Orłowska, K. (2017). Assessment of heavy metals contamination in surface layers of Roztocze National Park forest soils (SE Poland) by indices of pollution. *Chemosphere*, *168*, 839–850. https://doi.org/10.1016/j.chemosphere.2016.10.126

McArthur, Alan G. 1969. The Tasmanian bushfires of 7th February 1967 and associated fire behaviour characteristics. In: Mass Fire Symposium: The Technical Cooperation Programme, 1969 February 10–12; Canberra, Australia. Volume 1, Paper A7. Melbourne, Australia, Defence Standards Laboratories. 23 p.

McCarthy, G.J., Tolhurst, K.G., Wouters, M. Prediction of firefighting resources for suppression operations in Victoria's parks and forests. Department of Sustainability and Environment, Forest Science Centre: Vic, 2003, Research Report no. 56. Available online: https://www.ffm.vic.gov.au/__data/assets/pdf_file/0016/21067/Report-56-Prediction-of-firefighting-resources-for-suppression-operations-in-Victorias-Parks-and-Forests.pdf. (Access 12.07.2023)

McEvoy, A., Kerns, B.K., Kim, J.B. Hazards of risk: Identifying plausible community wildfire disasters in low-frequency fire regimes. In Forests, 2021, 12:934.

Mell, W., Jenkins, M. A., Gould, J., & Cheney, P. (2007). A physics-based approach to modelling grassland fires. International Journal of Wildland Fire, 16(1), 1-22.

Mell, W., Maranghides, A., et al. Numerical simulation and experiments of burning douglas fir trees. Combust. Flame, 2009, 156(10):2023–2041.

Mendes, A.B., Alvelos, F.P. Iterated local search for the placement of wildland fire suppression resources. In EUropean J. Oper. Res., 2022, 304:887–900.

Merganič, J., Fabrika, M. 2011

Merritt, W. S., Letcher, R. A., & Jakeman, A. J. (2003). A review of erosion and sediment transport models. Environmental Modelling & Software, 18(8–9), 761–799. http://dx.doi.org/10.1016/S1364-8152(03)00078-1.

Michalak, K. Auto-adaptation of genetic operators for multi-objective optimization in the firefighter problem. In Proceedings of the International Conference on Intelligent Data Engineering and Automated Learning, Salamanca, Spain, 10–12 September 2014, Springer: Cham, Switzerland, 2014, pp. 484–491.

Michalak, K. ED-LS—A heuristic local search for the multiobjective Firefighter Problem. Appl. Soft Comput. J. 2017, 59, 389–404.

Ministry for the Environment Manatū Mō Te Taiao, Good Practice Guide for Atmospheric Dispersion Modelling, www.mfe.govt.nz, ISBN: 0-478-18941-9 ME:522,Wellington, New Zealand, 2004.

Mirzabaev, A., J. Wu, J. Evans, F. García-Oliva, I.A.G. Hussein, M.H. Iqbal, J. Kimutai, T. Knowles, F. Meza, D. Nedjraoui, F. Tena, M. Türkeş, R.J. Vázquez, M. Weltz, 2019: Desertification. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D.C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. https://doi. Org/10.1017/9781009157988.005.

Missoula Fire Sciences Laboratory. 2023. FlamMap. Available online: https://www.firelab.org/project/flammap. (Accessed 09.09.2023)

Missoula Fire Sciences Laboratory. 2023. FSim-Wildfire Risk Simulation Software. Available online: https://www.firelab.org/project/fsim-wildfire-risk-simulation-software. (Accessed 08.09.2023)

Mitas, L. Mitasova, H. (1998). Distributed soil erosion simulation for effective erosion prevention, Water Resources Research, 34, 505-516

Mitasova, H., Hofierka, J., Zlocha, M., Iverson, L.R., (1996). Modeling topographic potential for erosion and deposition using GIS. Int. Journal of Geographical Information Science, 10(5), 629-641.

Mitsopoulos I, Mallinis G, Arianoutsou M (2015) Wildfire risk assessment in a typical Mediterranean wildland-urban interface of Greece. *Environ Manag* 55:900–915.

Mitsopoulos, I. and Dimitrakopoulos, A. 2014. Estimation of canopy fuel characteristics of Aleppo pine (*Pinus halepensis* Mill.) forests in Greece based on common stand parameters. *Eur. J. For. Res.* 133:73–79.

Mitsopoulos, I. and Xanthopoulos, G. 2016. Effect of stand, topographic, and climatic factors on the fuel complex characteristics of Aleppo (*Pinus halepensis* Mill.) and Calabrian (*Pinus brutia* Ten.) pine forests of Greece. *For. Ecol. Manag.* 360: 110–121.

Mitsopoulos, I.D. and Dimitrakopoulos, A.P. 2007. Allometric equations for crown fuel biomass of Aleppo pine (*Pinus halepensis* Mill.) in Greece. *Int. J. Wildl. Fire.* 16:642–647.

Mohammad Pishahang, Enrique Droguett, Marilia Ramos, Ali Mosleh (2022). Wildfire Egress Model and Simulation Platform. Report GIRS-2022-03. DOI:10.34948/G4159S. Prepared for Pacific Gas and Electric Company

Mohammad Pishahang, Enrique Droguett, Marilia Ramos, Ali Mosleh (2022). Wildfire Egress Model and Simulation Platform. Report GIRS-2022-03. DOI:10.34948/G4159S. Prepared for Pacific Gas and Electric Company

Mohammadi F, Bavaghar MP, Shabanian N (2014) Forest fire risk zone modeling using logistic regression and GIS: an Iranian case study. *Small-scale Forestry* 13:117–125.

Molina, J.R., y Silva, F.R. and Herrera, M.A. 2011. Potential crown fire behavior in *Pinus pinea* stands following different fuel treatments. *For. Syst.* 20:266–267.

Molina-Terrén, D.M., Martínez-López, E.R., Garcia-Marco D. Farsite simulations for cost-efficient wildland fire planning: Case studies in Spain. In Forest Ecology and Management, 2006, Vol. 234, Supplement, p. S217

Monia Santini, Gabriele Caccamo, Alberto Laurenti, Sergio Noce, Riccardo Valentini, A multi-component GIS framework for desertification risk assessment by an integrated index, Applied Geography, Volume 30, Issue 3, 2010, Pages 394-415, ISSN 0143-6228, https://doi.org/10.1016/j.apgeog.2009.11.003.

Monteiro, A., Corti, P., San Miguel-Ayanz, J., Miranda, A. I., & Borrego, C. (2014). The EFFIS forest fire atmospheric emission model: Application to a major fire event in Portugal. Atmospheric Environment, 84, 355-362.

Moreaux, V., Martel, S., Bosc, A., Picart, D., Achat, D., Moisy, C., Aussenac, R., Chipeaux, C., Bonnefond, J.-M., Figuères, S., Trichet, P., Vezy, R., Badeau, V., Longdoz, B., Granier, A., Roupsard, O., Nicolas, M., Pilegaard, K., Matteucci, G., … Loustau, D. (2020). Energy, water and carbon exchanges in managed forest ecosystems: Description, sensitivity analysis and evaluation of the INRAE GO+ model, version 3.0. Geoscientific Model Development, 13(12), 5973–6009.

Morgan, R. P. C. (2005). Soil erosion and conservation (3rd ed.), Blackwell.

Morgan, R. P. C., Morgan, D. D. V., & Finney, H. J. (1984). A predictive model for the assessment of soil erosion risk. Journal of Agricultural Engineering Research, 30, 245–253. https://doi.org/10.1016/S0021-8634(84)80025-6

Morgan, R.P.C., (2001). A simple approach to soil loss prediction: A Revised Morgan-Morgan-Finney model. Catena, 44, 305–322.

Morris, G.A. A simple method for computing spotting distances from wind-driven surface fires. Ogden, UT: USDA Forest Service, Intermountain Research Station, Research Note INT-RN-374, 1987.

Morton, B.R. Modeling fire plumes. In Symposium (International) on Combustion, 1965, 10(1):973-982.

Morvan, D., Accary, G., et al. A 3D physical model to study the behavior of vegetation fires at laboratory scale. In Fire Saf. J., 2018, 101:39–52. doi:10.1016/j.firesaf.2018.08.011.

MTBS. 2023. QGIS Fire Mapping Tool. Available online: https://www.mtbs.gov/qgis-fire-mapping-tool. (Access 22.08.2023)

Mueller, E.V, Skowronski, N.S., Clark, K.L., Gallagher, M.R., Mell, W.E., Simeoni, A., Hadden, R. M. Detailed physical modeling of wildland fire dynamics at field scale - An experimentally informed evaluation. Fire Safety Journal, 2021, 120:103051.

Mueller, E.V., Skowronski, N. et al. Local measurements of wildland fire dynamics in a field-scale experiment. In Combust. Flame, 2018, 194:452–463.

Mueller, E.V., Skowronski, N. et al. Utilization of remote sensing techniques for the quantification of fire behavior in two pine stands. In FireSaf. J., 2017, 91:845–854. doi:10.1016/j.firesaf.2017.03.076.

Mulder, T., Syvitski, J.P.M., (1996). Climatic and Morphologic Relationships of Rivers: Implications of Sea-Level Fluctuations on River Loads. The Journal of Geology, 104 (5), 509–523.

Müller, G. (1969). Index of geoaccumulation in sediments of the Rhine River. *GeoJournal*, *2*(3), 108–118.

Muñoz-Rojas, M. (2018). Soil quality indicators: critical tools in ecosystem restoration. *Current Opinion in Environmental Science & Health*, *5*, 47–52. https://doi.org/10.1016/J.COESH.2018.04.007

Murray, A.T. Spatial restrictions in harvest scheduling. In For. Sci., 1999, 45:45-52. doi: 10.1093/forestscience/45.1.45

N.C Coops, R.H Waring, J.J Landsberg. (1998). Assessing forest productivity in Australia and New Zealand using a physiologically based model driven with averaged monthly weather data and satellite-derived estimates of canopy photosynthetic capacity. Forest Ecology and Management, Volume 104, Issues 1–3, Pages 113-127.

Nagy, R.C.; Fusco, E.; Bradley, B.; Abatzoglou, J.T.; Balch, J. Human-related ignitions increase the number of large wildfires across U.S. Ecoregions. In Fire, 2018, 1:4.

Natural Resources Canada. 2023. Canadian Wildland Fire Information System. Available online: https://cwfis.cfs.nrcan.gc.ca/background. (Accessed 21.08.23)

Natural Resources Canada. Burn-P3 Version 4.7 User's manual. 2017, 59 p.

Natural Resources Conservation Services (NRCS), (1986). Urban hydrology for small watersheds, Technical Release 55, 210-VI-TR-55, 728. US Department of Agriculture: Washington DC, p. 2-1 to F-3.

Nearing, M. A., and S. C. Parker. 1994. Detachment of soil by flowing water under turbulent and laminar conditions. Soil Sci. Soc. Am. J. 58(6): 1612–1614.

Nelson, R.M. Jr. Prediction of diurnal change in 10-h fuel stick moisture content. Canadian Journal of Forest Research, 2000, 30(7):1071-1087. doi:10.1139/x00-032.

NFPA 1051 Standard for Wildland Fire Fighter Professional Qualifications, 2007 Edition.

NFPA 1140 Standard for Wildland Fire Protection, 2022 Edition.

Niinimäki, S., Tahvonen, O., Mäkelä, A. Applying a process-based model in Norway spruce management. In For Ecol Manag., 2012, 265:102–15.

Noonan-Wright, E.K., Opperman, T.S., Finney, M.A., et al. Developing the US Wildland fire decision support system. In Journal of Combustion, 2011, 14:168473.

Noss, R.F., Cooperrider, A.Y. Saving nature's legacy: Protecting and Restoring Biodiversity. Island Press, Washington, D.C., 1994 443, p.

Ntaimo, L., Arrubla, J.A.G., Stripling, C., Young, J., Spencer, T. A stochastic programming standard response model for wildfire initial attack planning. In Can. J. For. Res., 2012, 42:987–1001.

Ntaimo, L., Gallego-Arrubla, J.A., Gan, J., Stripling, C., Young, J., Spencer, T. A Simulation and Stochastic Integer Programming Approach to Wildfire Initial Attack Planning. In For. Sci., 2013, 59:105–117.

Nuruddin M.F., Ullah Khan S., Shafiq N., Ayub T. Strength prediction models for PVA fiber-reinforced high strength concrete. In Journal of Materials in Civil Engineering, 2015, 27:2–16.

NWCG. 2022. Incident Response Pocket Guide – PMS 461. Available online: https://www.nwcg.gov/sites/default/files/publications/pms461.pdf. (Access 24.06.2023)

Ohlson, DW, Berry, TM, Gray, RW, Blackwell, BA, Hawkes, BC Multi-Attribute Evaluation of Landscape-Level Fuel Management to Reduce Wildfire Risk. Forest Policy and Economics, 8 (8): 824-837.

Oliver, T. H., Heard, M. S., Isaac, N. J. B., Roy, D. B., Procter, D., Eigenbrod, F., Freckleton, R., Hector, A., Orme, C. D. L., Petchey, O. L., Proença, V., Raffaelli, D., Suttle, K. B., Mace, G. M., Martín-López, B., Woodcock, B. A., & Bullock, J. M. (2015). Biodiversity and Resilience of Ecosystem Functions. *Trends in Ecology and Evolution*, *30*(11), 673–684. https://doi.org/10.1016/j.tree.2015.08.009

Ollinger, S. V., Aber, J. D., Reich, P. B., & Freuder, R. J. (2002). Interactive effects of nitrogen deposition, tropospheric ozone, elevated CO2, and land use history on the carbon dynamics of northern hardwood forests. Global Change Biology, 8(6), 545–562.

Olson, D.L. Data mining in business services. In Service Business, 2007, 1(3):181–193. doi:10.1007/s11628-006-0014-7.

Omi, PN (1996). The Role of Fuel Brakes . In: 17th Annual Conference on Forest Vegetation Management , pp. 89-96, Redding, CA.

Omi, PN and Kalabokidis, KD (1998). Fuels Modification to Reduce Large Fire Probability . In: 14 th conference on fire and forest meteorology (Viegas, DX, ed.), Pp. 2073-2088, Coimbra, Portugal.

Önal, H., Briers, R.A. Optimal selection of a connected reserve network. In Oper. Res., 2006, 54:402-403. doi: 10.1287/opre.1060.0272.

Orazio, C., Tomé, M., Colin, A., Diez Casero, J., Jactel, H., Mendes, A., Martinez, I. FORSEE PROJECT: A Network of 10 Pilot Zones to Test and Improve Criteria and Indicators for Sustainable Forest Management at Regional Level in Atlantic European Countries; Rationale and Workplan Interim report; IEFC: Cestas, France, 2006.

Özçelik, R., Diamantopoulou, M.J., Crecente-Campo, F., Eler, U. Estimating Crimean juniper tree height using nonlinear regression and artificial neural network models. In Forest Ecology and Management, 2013, 306(10):52-60. doi: 10.1016/j.foreco.2013.06.009.

Pacific Northwest Research Station. Wildland Urban Interface Fire Dynamics Simulator (WFDS). 2018. Available online: https://www.fs.usda.gov/research/pnw/projects/wfds. (Access 22.09.2023)

Palahí M, Pukkala T, Kasimiadis D, Poirazidis K, Papageorgiou AC (2008) Modelling site quality and individual-tree growth in pure and mixed *Pinus brutia* stands in north-east Greece. *Ann For Sci* 65:501.

Palmetzhofer, D., Stampfer, K., Limbeck-Lilienau, B. Application of the spatial decision support system CONES for the regeneration planning in mountain forests. In Cable Yarding Suitable for Sustainable Forest Management, 23. sept. 2004, Idrija, Slovenia.

Panagopoulos, T. Linking forestry, sustainability, and aesthetics. In Ecol. Econ., 2009, 68:2485-2489. doi: 10.1016/j.ecolecon.2009.05.006.

Panagos, P., Karydas, C.G., Gitas, I.Z., Montanarella, L., 2012. Monthly soil erosion monitoring based on remotely sensed biophysical parameters: a case study in Strymonas river basin towards a functional pan-European service, International Journal of Digital Earth 5 (6), 461-487

Pandey, A.; Himanshu, S.; Mishra, S.; Catena, V.S. Physically based soil erosion and sediment yield models revisited. CATENA 2016, 147, 595–620.

Park, Y.-S., Chung, Y.-J. Hazard rating of pine trees from a forest insect pest using artificial neural networks. In Forest Ecology and Management, 2006, 222(1-3):222-233. doi: 10.1016/j.foreco.2005.10.009.

Parton, W. J., Schimel, D. S., Cole, C. V., & Ojima, D. S. (1987). Analysis of Factors Controlling Soil Organic Matter Levels in Great Plains Grasslands. Soil Science Society of America Journal, 51(5), 1173–1179. https://doi.org/10.2136/sssaj1987.03615995005100050015x

Pejman, A., Nabi Bidhendi, G., Ardestani, M., Saeedi, M., & Baghvand, A. (2015). A new index for assessing heavy metals contamination in sediments: A case study. *Ecological Indicators*, *58*, 365–373. https://doi.org/10.1016/J.ECOLIND.2015.06.012

Peng, C., Liu, J., Dang, Q., Apps, M. J., & Jiang, H. (2002). TRIPLEX: A generic hybrid model for predicting forest growth and carbon and nitrogen dynamics. Ecological Modelling, 153(1), 109–130.

Perez-Marin, A.M.; Vendruscolo, J.; Zárate-Salazar, J.R.; De Araújo Queiroz, H.A.; Magalhães, D.L.; Menezes, R.S.C.; Fernandes, I.M. Monitoring Desertification Using a Small Set of Biophysical Indicators in the Brazilian Semiarid Region. Sustainability 2022, 14, 9735. https://doi.org/10.3390/su14159735.

Peringer, A., Siehoff, S., Chételat, J., Spiegelberger, T., Buttler, A., & Gillet, F. (2013). Past and future landscape dynamics in pasture-woodlands of the Swiss Jura Mountains under climate change. Ecology and Society, 18(3).

Peterson, D., Finney, M., Skinner, C., Kaufmann, M., Johnson, M., Shepperd, W., Harrington, M., Keane, R., McKenzie, D., Reinhardt, E., Ryan, K., 2004. Science Basis for Changing Forest Structure to Modify Wildfire Behavior and Severity. In: Russell T. Graham, Sarah McCaffrey, Theresa B. Jain, Eds. U.S.D.A. Rocky Mountain Research Station, General Technical Report RMRS-GTR-120, p. 52.

Pietsch, S. A., Hasenauer, H., & Thornton, P. E. (2005). BGC-model parameters for tree species growing in central European forests. Forest Ecology and Management, 211(3), 264–295. https://doi.org/10.1016/j.foreco.2005.02.046

Pietsch, S., Bednar, J.E., Mosnier, A., & Obersteiner, M. (2015). Probabilistic Spatial and Temporal Resilience Landscapes for the Congo Basin. In: Systems Analysis 2015 - A Conference in Celebration of Howard Raiffa, 11-13 November, 2015, Laxenburg, Austria.

Pimm, S. L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R., & Loarie, S. (2015). Emerging Technologies to Conserve Biodiversity. *Trends in Ecology and Evolution*, *30*(11), 685–696. https://doi.org/10.1016/j.tree.2015.08.008

Pimont, F., Dupuy, J.-L., Linn, R.R. Fire effects on the physical environment in the WUI using FIRETEC. In Adv. For. Fire Res. Proc from 7th Int. Conf. For. Fire Res., University of Coimbra: Coimbra, Portugal, 2014.

Pisso, I., Sollum, E., Grythe, H., Kristiansen, N. I., Cassiani, M., Eckhardt, S., ... & Stohl, A. (2019). The Lagrangian particle dispersion model FLEXPART version 10.4. Geoscientific Model Development, 12(12), 4955-4997.

Pokyn prezidenta Hasičského a záchranného zboru č. 39/2003 o obsahu a o postupe pri spracúvaní dokumentácie o zdolávaní požiarov / Instruction No. 39/2003 of the President of the Fire and Rescue Corps on the content and procedure for the processing of firefighting documentation. [In Slovak]

Portoghesi, L., Alivernini, A., Cimini, D., Bertani, R., Marchetti, M., Corona, P. FORFUN: a computerized tool to create a ranking of relative importance for forest functions at stand scale. In: Proceedings of the Implementation of DSS Tools into the forestry practice, Reviewed Conference Proceedings, Technical University Zvolen, Slovakia, 2013, pp. 93–99.

Pourghasemi HR, Beheshtirad M, Pradhan B (2016) A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping. *Geomat Nat Hazards Risk* 7:861–885.

Prichard, S. J., Ottmar, R. D., & Anderson, G. K. (2006). Consume 3.0 user's guide. Pacific Northwest Research Station, Corvallis, Oregon.

Published:29 May 2023https://doi.org/10.1098/rstb.2022.0182

Pukkala, T. Dealing with Ecological Objectives in the Monsu Planning System. In Silva Lusitana, 2004, nº especial:1 - 15.

Pukkala, T., Lahde, E., Laiho, O. Optimizing the structure and management of uneven-sized stands of Finland. In Forestry, 2010, 83(2):129–42.

Pukkala, T., Nuutinen, T., Kangas, J. Integrating scenic and recreational amenities into numerical forest planning. In Landsc. Urban Plan., 1995, 32:185–195.

PYROLOGIX, 2023. Nexus 2.1 software. Available online: https://pyrologix.com/downloads/. (Accessed 16.09.2023)

QGIS. 2023. About QGIS. Available online: https://www.qgis.org/. (Access: 28.09.2023)

Qingjie, G., Deng, J., Yunchuan, X., Qingfei, W., & Liqiang, Y. (2008). Calculating Pollution Indices by Heavy Metals in Ecological Geochemistry Assessment and a Case Study in Parks of Beijing. *Journal of China University of Geosciences*, *19*(3), 230–241.

Ramos, N., de Souza, C.C., de Rezende, P.J. A matheuristic for the firefighter problem on graphs. In Int. Trans. Oper. Res., 2020, 27:739–766.

Raptis, D., Kazana, V., Kazaklis, A. and Stamatiou, C. 2018. A Crown Width-Diameter Model for Natural Even-Aged Black Pine Forest Management. *Forests* 9, 610.

Raptis, D.I., Kazana, V., Kazaklis, A. and Stamatiou, C. 2021. Mixed-effects height–diameter models for black pine (*Pinus nigra* Arn.) forest management. *Trees* 35 (4): 1167–1183.

Raptis, D.I., Kazana, V., Kechagioglou, S., Kazaklis, A., Stamatiou, C., Papadopoulou, D. and Tsitsoni T. 2022. Nonlinear Quantile Mixed-Effects Models for Prediction of the Maximum Crown Width of *Fagus sylvatica* L., *Pinus nigra* Arn. and *Pinus brutia* Ten. *Forests* 13(4):499.

Raza A., Ahrends H., Habib-Ur-Rahman M., Gaiser T., (2021) Modeling Approaches to Assess Soil Erosion by Water at the Field Scale with Special Emphasis on Heterogeneity of Soils and Crops. Land, 10 (4), 1-35.

Redsven, V., Hirvelä, H., Härkönen, K., Salminen, O., Siitonen, M.''MELA2007 Reference Manual''. Metsäntutkimuslaitos - The Finnish Forest Research Institute, 2007, 642 p.

Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balmes, J. R., & Elliott, C. T. (2016). Critical review of health impacts of wildfire smoke exposure. Environmental health perspectives, 124(9), 1334-1343.

Reinhardt, E.D., Crookston, N.L. The Fire and Fuels Extension to the Forest Vegetation Simulator. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-116, 2003.

Reisen Fabienne, Duran Sandra M., Flannigan Mike, Elliott Catherine, Rideout Karen (2015) Wildfire smoke and public health risk. International Journal of Wildland Fire 24, 1029-1044.

Reisner, J., Bossert, J., Winterkamp, J. Numerical Simulations of Two Wildfire Events Using a Combined Modeling System (HIGRAD/BEHAVE); No. LA-UR-97-4036; CONF-980121; Los Alamos National Lab.: Los Alamos, NM, USA, 1998.

Reisner, J., Wynne, S., Margolin, L., Linn, R. Coupled atmospheric-fire modeling employing the method of averages. In Mon. Weather Rev. 2000, 128:3683–3691.

Reisner, J.M., Wynne, S., Margolin, L., Linn, R.R. Coupled atmospheric–fire modeling employing the method of averages. In Mon. Weather Rev., 2000, 128: 3683–3691.

Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC (1997) Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). Agriculture Handbook No. 703, USDA-ARSSharpley, A.N. and Williams J.R. (Editors), (1990). EPIC-Erosion/Productivity Impact Calculator. 1. Documentation. USDA Tech. Bull, 1768: 235 pp.

Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C. (1996). Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation. USDA Agric. HB No. 703, Washington DC, USA.

Renard, K.G., Foster, G.R., Weesies, G.A., Porter, J.P. (1991). RUSLE: Revised Universal Soil Loss Equation. J. Soil Water Conserv. 46 (1), 30−33.

Renard, K.G., Foster, G.R., Yoder, D.C., McCool, D.K. (1994). RUSLE revisited: Status, questions, answers, and the future. J. Soil Water Conserv. 49 (3), 213−220.

Republic of Croatia (2023a), https://civilna-zastita.gov.hr/sruuk-sustav-za-rano-upozoravanje-i-upravljanje-krizama/7097

Republic of Croatia (2023b), https://civilna-zastita.gov.hr/rano-upozoravanje-i-uzbunjivanje/144

Reynolds, K.M., Hessburg, P.F. 2014. An overview of the Ecosystem Management Decision-Support System. Chapter 1 in Reynolds, K.M., P.F. Hessburg, and P.S. Bourgeron (eds). Decision Support for Environmental Management: Applications of the Ecosystem Management Decision Support System. Berlin: Springer, 2014, pp. 3-22.

Rideout, D.B., Kirsch, A.G., Wei, Y., Kernohan, N.J. STARFire: Strategic Budgeting and planning for wildland fire management. In Park Sci., 2017, 33:34–41.

Riebau, A. R., Fox, D. G., Sestak, M. L., Dailey, B., & Archer, S. F. (1988). Simple approach smoke estimation model. Atmospheric Environment (1967), 22(4), 783-788.

Riley, K.L., Grenfell, I.C., Shaw, J.D., Finney, M.A. TreeMap 2016 Dataset Generates CONUS-Wide Maps of Forest Characteristics Including Live Basal Area, Aboveground Carbon, and Number of Trees per Acre Get access Arrow. In Journal of Forestry, 2022, 120(6):607–632. doi:10.1093/jofore/fvac022.

Ríos-Mercado, R.Z. An Integrated Framework for Control and Management of Forest Fires Using Potential Fire Risk Indices. Ph.D. Thesis, Universidad de Córdoba, Córdoba, Spain, 2020.

Rocky Mountain Research Station. 2014. Arc Fuels. Available online: https://www.fs.usda.gov/research/rmrs/projects/arcfuels. (Access 12.09.2023)

Rodríguez y Silva, F., O'Connor, C.D., Thompson, M.P., Molina Martínez, J.R., Calkin, D.E. Modelling suppression difficulty: Current and future applications. In Int. J. Wildland Fire, 2020, 29:739–751.

Rodríguez-Veiga, J., Gomez-Costa, I., Guinzo-Villamayor, M.J., Casas-Mezdez, B., Sáiz-Diaz, J.L. Assignment problems in wildfire suppression: Models for optimization of aerial resource logistics. In For. Sci. 2018, 64:504–514.

Rodríguez-Veiga, J., Guinzo-Villamayor, M.J., Casas-Méndez, B. An integer linear programming model to select and temporally allocate resources for fighting forest fires. In Forests, 2018, 9:583.

Roitman, I., Vieira, L.C.G., Jacobson, T.K.B., Bustamante, M.M.C., Marcondes, N.J.S., Cury, K., Estevam, L.S., Ribeiro, R.J.C., Ribeiro, V., Stabile, M.C.C., Filho, R.J.M., Avila, M.L. Rural environmental registry: an innovate model for land-use and environmental policies. In Land Use Policy, 2018, 76:95-102. doi: 10.1016/j.landusepol.2018.04.037

Romero-Calcerrada R, Barrio-Parra F, Millington JDA., Novillo C J (2010) Spatial modelling of socioeconomic data to understand patterns of human-caused wildfire ignition risk in the SW of Madrid (central Spain). Ecol Modell 221: 34-45.

Romero-Calcerrada R, Novillo J, Millington JDA, Gomez-Jimenez I (2008) GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain). Landsc Ecol 23:341–354.

Ronchi E., and Gwynne S. (2019). https://link.springer.com/referenceworkentry/10.1007/978-3-319-51727-8_121-1

Rönnqvist, M, D'Amours, S., Weintraub, A., Jofre, A., Gunn, E., Haight, R.G., Martell, D., Murray, A.T., Romero, C. Operations research challenges in forestry: 33 open problems. In Ann. Oper. Res., 2015, 232:11–40. doi: 10.1007/s10479-015-1907-4.

Rönnqvist, M., D'Amours, S., Weintraub, A., Jofre, A., Gunn, E., Haight, R.G., Martell, D., Murray, A.T., Romero, C. Operations Research challenges in forestry: 33 open problems. In Ann. Oper. Res., 2015, 232:11–40.

Roozbeh, I., Ozlen, M., Hearne, J.W. An Adaptive Large Neighbourhood Search for asset protection during escaped wildfires. In Comput. Oper. Res., 2018, 97:125–134.

Rossi, J.L., Simeoni, A., Moretti, B., Leroy-Cancellieri, V. An analytical model based on radiative heating for the determination of safety distances for wildland fires. In Fire Safety Journal, 2011, 46:520–527. doi:10.1016/J.FIRESAF.2011.07.007.

Roth (1914) Roth, F. 1914. Forest regulation, or the preparation and development of forest working plans. Michigan Manual of Forestry. Published by the author. Ann Arbo, Michigan, 1914, 218 p.

Rothermel, R. A Mathematical Model for Predicting Fire Spread in Wildland Fuels; U.S. Department of Agriculture, Intermountain Forest and Range Experiment Station: Ogden, UT, USA, 1972; p. 40.

Rothermel, R. C. 1972. A mathematical model for predicting fire spread in wildland fuels. Res. Pap. INT-115. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 40 p.

Rothermel, R. C. 1983. How to predict the spread and intensity of forest and range fires. Gen. Tech. Rep. INT-143. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 161 p.

Rothermel, R. C. 1991. Predicting behavior and size of crown fires in the Northern Rocky Mountains. Res. Pap. INT-438. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 46 p.

Rothermel, R.C. A Mathematical Model for Predicting Fire Spread in Wildland Fuels; U.S. Department of Agriculture, Intermountain Forest and Range Experiment Station: Ogden, UT, USA, 1972; p. 40

Rothermel, R.C. A mathematical model for predicting fire spread in wildland fuels, Res. Pap. INT-115, 40 pp., U.S. Dep. of Agric. For. Serv., Ogden, Utah, 1972.

Rothermel, R.C. How to predict the spread and intensity of forest and range fires. Ogden, UT: USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-143, 1983.

Rothermel, R.C. Predicting behavior and size of crown fires in the northern Rocky Mountains. Res. Pap. INT-RP-438. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station, 1991, 46 p.

Rothermel, Richard C. and Anderson, Hal E. 1966. Fire spread characteristics determined in the laboratory. Res. Pap. INT-30. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 34 p.

Running, S. W., & Gower, S. T. (1991). FOREST-BGC, A general model of forest ecosystem processes for regional applications. II. Dynamic carbon allocation and nitrogen budgets. Tree Physiology, 9(1–2), 147–160.

Ryan, K.C., Amman, G.D. Interactions between fire-injured trees and insects in the greater Yellowstone area. In ‘Plants and their environments: Proceedings of the 1st Biennial Scientific Conference on the Greater Yellowstone Ecosystem’, 16–17 September 1991, Yellowstone National Park, WY. (Ed. DG Despain), Denver, CO: US Department of the Interior, National Park Service, Natural Resources Publication Office, Technical Report NPS/NRYELL/NRTR, 1994, pp. 259–271.

Ryan, K.C., Reinhardt, E.D. Predicting post fire mortality of seven western conifers. In Canadian Journal of Forest Research, 1988, 18:1291–1297.

Safi, Y., Bouroumi, A. Prediction of Forest Fires Using Artificial Neural Networks. Applied Mathematical Sciences, 2013, 7(6):271-286.

Sakellariou, S., Parisien, M.A., Flannigan, M., Wang, X., de Groot, B., Tampekis, S., Samara, F., Sfougaris, A., Christopoulou, O. Spatial planning of fire-agency stations as a function of wildfire likelihood in Thasos, Greece. In Sci. Total Environ., 2020, 729:139004.

Sakellariou, S., Samara, F., Tampekis, S., Sfougaris, A., Christopoulou, O. Development of a Spatial Decision Support System (SDSS) for the active forest-urban fires management through location planning of mobile fire units. In Environ. Hazards, 2020, 19:131–151.

Salvia R., Gianluca E., Sabato V., and Luca S. (2019). Desertification Risk and Rural Development in Southern Europe: Permanent Assessment and Implications for Sustainable Land Management and Mitigation Policies. Land 8, no. 12: 191. https://doi.org/10.3390/land8120191.

Sampson, D. A., Janssens, I. A., Curiel Yuste, J., & Ceulemans, R. (2007). Basal rates of soil respiration are correlated with photosynthesis in a mixed temperate forest. Global Change Biology, 13(9), 2008–2017.

Sandberg, D. V., & Peterson, J. (1984). A source strength model for prescribed fires in coniferous logging slash. In Annual Meeting, Air Pollution Control Association, Pacific Northwest Section. Reprint (Vol. 84).

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., Strobl, P., Liberta, G., ... & Amatulli, G. (2012). Comprehensive monitoring of wildfires in Europe: the European forest fire information system (EFFIS). In Approaches to managing disaster-Assessing hazards, emergencies and disaster impacts. IntechOpen.

Sarah A. Grajdura, Sachraa G. Borjigin, and Deb A. Niemeier. (2020). Agent-based wildfire evacuation with spatial simulation: a case study. In Proceedings of the 3rd ACM SIGSPATIAL International Workshop on GeoSpatial Simulation (GeoSim '20). Association for Computing Machinery, New York, NY, USA, 56–59. https://doi.org/10.1145/3423335.3428169

Schelhaas M.-J., Eggers J., Lindner M., Nabuurs G.-J., Päivinen R., Schuck A., Verkerk P.J., van der Werf D.C. & Zudin S. (2007). Model documentation for the European Forest Information Scenario model (EFISCEN 3.1.3). Alterra report 1559.

Schelhaas, M.-J., Eggers, J., Lindner, M., Nabuurs, G.J., Päivinen, R., Schuck, A., Verkerk, P.J., Werf, D.C. van der, Zudin, S. (2007). Model documentation for the European Forest Information Scenario model (EFISCEN 3.1.3). Alterra report 1559 and EFI technical report 26.

Schelhaas, M.J., Nabuurs, G.J., Verkerk, P.J., Hengeveld, G., Packalen, T., Sallnäs, O., Pilli, R., Grassi, G., Forsell, N., Frank, S. et al. (2018). Forest Resource Projection Tools at the European Level. In: Barreiro S.M., Schelhaas M.-J., McRoberts R.E., Kändler G. (eds) Forest Inventory-based Projection Systems for Wood and Biomass Availability. Managing Forest Ecosystems 29: 49-68.

Scheller, R.M., Domingo, J.B., Sturtevant, B.R., Williams, J.S., Rudy, A., Gustafson, E.J., Mladenoff, D.J. Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. In Ecological Modelling, 2007, 201(3-4):409-419.

Scherer, G., Zabowski, D., Java, B., Everett, R. (2000). Timber Harvesting Residue Treatment. Part II. Understory Vegetation Response. Forest Ecology and Management, 126 (1): 35-50.

Scheurman, P. (1977) Modelling the Information Space in Physical Storage at Different Levels of Detail. The In Computer Journal, 1977, 20(3):248-256.

Schröder J, Röhle H, Gerold D, Münder K (2007) Modeling individual-tree growth in stands under forest conversion in East Germany. *Eur J Forest Res* 126:459–472.

Scire, J. S. (2000). CALPUFF: Overview of capabilities. In 'Technical Highlights of EPA's 7th Conference on Air Pollution Modeling', 1 August 2000.(North Carolina State University)

Scott, J.H. 1999. NEXUS: a system for assessing crown fire hazard. Fire Manage. Notes 59 (2), 20–24.

Scott, J.H. and Reinhardt, E.D. 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. USDA Forest Service Research Paper RMRS-RP-29.

Scott, J.H. and Reinhardt, E.D. 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. USDA For. Serv. Res. Pap. RMRS-RP-29.

Scott, J.H. and Reinhardt, E.D. 2007. Effects of Alternative Treatments on Canopy Fuel Characteristics in Five Conifer Stands. USDA Forest Service Gen. Tech. Rep. PSW-GTR-203.

Scott, J.H. NEXUS: a system for assessing crown fire hazard. In Fire Management Notes, 1999, 59(2):20-24.

Scott, J.H., Reinhardt, E.D. 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. Res. Pap. RMRS-RP-29. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2001, 59 p.

Scrinzi, G., Marzullo, L., Galvagni, D. Development of a neural network model to update forest distribution data for managed alpine stands. In Ecological Modelling, 2007, 206(3–4):331-346. doi: 10.1016/j.ecolmodel.2007.04.001

Seiler, W., & Crutzen, P. J. (1980). Estimates of gross and net fluxes of carbon between the biosphere and the atmosphere from biomass burning. Climatic change, 2(3), 207-247.

Sessions, J. Solving for Habitat Connections as a Steiner Network Problem. In Forest Science, 1992, 38(1):203-207.

Sestak, M.L.; Marlatt, W.E.; Riebau, A.R. 1989. VALBOX: ventilated valley box model. Unpublished report.

Setiawan I, Mahmud A, Mansor S, Mohamed Shariff A, Nuruddin A (2004) GIS-grid-based and multi-criteria analysis for identifying and mapping peat swamp forest fire hazard in Pahang, Malaysia. Disaster Prevention Management: *An Int J* 13:379–386.

Shahidi, A., Ramezanian, R., Shahparvari, S. A greedy heuristic algorithm to solve a VRP-based model for planning and coordinating multiple resources in emergency response to bushfires. In Sci. Iran., 2022, 22673.

Shahparvari, S., Abbasi, B., Chhetri, P., Abareshi, A. Fleet routing and scheduling in bushfire emergency evacuation: A regional case study of the Black Saturday bushfires in Australia. In Transp. Res. Part D, 2019, 67:703–722.

Shahparvari, S., Bodaghi, B., Roozbeh, I., Mohammadi, M., Soleimani, H., Chhetri, P. A cooperative (or coordinated) multi-agency response to enhance the effectiveness of aerial bushfire suppression operations. In Int. J. Disaster Risk Reduct., 2021, 61:102352.

Shang, BZ, He, HS, Crow, TR, Shifley, SR (2004). Fuel Load Reductions and Fire Risk in Central Hardwood Forests of the United States: A Spatial Simulation Study. Ecological Modeling, 180 (1): 89-102.

Sheppard, W.F. "Interpolation" . In Chisholm, Hugh (ed.). Encyclopædia Britannica. Vol. 14 (11th ed.). Cambridge University Press, 2011, pp. 706–710.

Shi, G., Yan, H., Zhang, W., Dodson, J., Heijnis, H., Burrows, M. Rapid warming has resulted in more wildfires in northeastern Australia. In Sci. Total Environ., 2021, 771:144888.

Shonkwiler, R.W., Mendivil, F. Explorations in Monte Carlo Methods. Springer, Dordrecht Springer, 2009, 243 p.

Shulan Sun, Shuai Ouyang, Yanting Hu, Zhonghui Zhao, Meixian Liu, Liang Chen, Yelin Zeng, Changhui Peng, Xiaolu Zhou, Wenhua Xiang. (2023). rTRIPLEXCWFlux: An R package for carbon–water coupling model to simulate net ecosystem productivity and evapotranspiration in forests. Environmental Modelling & Software, Volume 162, 105661.

Siam et al., (2022). https://par.nsf.gov/servlets/purl/10313601

Sierksma, G., Zwols, Y. Linear and Integer Optimization: Theory and Practice (3rd ed.). CRC Press, 2015, p. 686. ISBN 978-1498710169.

Siqiong Zhou, Ayca Erdogan, A spatial optimization model for resource allocation for wildfire suppression and resident evacuation, (2019). Computers & Industrial Engineering, Volume 138, 106101, ISSN 0360-8352, https://doi.org/10.1016/j.cie.2019.106101. (https://www.sciencedirect.com/science/article/pii/S0360835219305704)

Sirca C, Salis M, Arca B, Duce P, Spano, D (2018) Assessing the performance of fire danger indexes in a Mediterranean area. *iForest - Biogeosciences and Forestry* 11: 563-571.

Skowronski, N.S., Clark, K.L., Duveneck, M., Hom, J. Three-dimensional canopy fuel loading predicted using upward and downward sensing LiDAR systems. In Remote Sensing of Environment, 2011, 115(2):703-714. doi: 10.1016/j.rse.2010.10.012.

Smith, CT, Lowe, AT, Skinner, MF, Beets, PN, Schoenholtz, SH, Fang, S. (2000). Response of Radiata Pine Forests to Residue Management and Fertilization across a Fertility Gradient in New Zealand. Forest Ecology and Management, 138 (1-3): 203-223.

Soininen, J., Passy, S., & Hillebrand, H. (2011). The relationship between species richness and evenness: a meta-analysis of studies across aquatic ecosystems. Oecologia, 169(3), 803-809. https://doi.org/10.1007/s00442-011-2236-1

Song H, Peng C, Zhang K, Zhu Q. (2022). Integrating major agricultural practices into the TRIPLEX-GHG model v2.0 for simulating global cropland nitrous oxide emissions: Development, sensitivity analysis and site evaluation. Sci Total Environ. 843:156945. doi: 10.1016/j.scitotenv.2022.156945.

Steffensen, J. F. Interpolation. (Second ed.). Dover Publications, Mineola, N.Y., 2006, p. 248. ISBN 978-0-486-15483-1.

Stein, A. F., Draxler, R. R., Rolph, G. D., Stunder, B. J., Cohen, M. D., & Ngan, F. (2015). NOAA's HYSPLIT atmospheric transport and dispersion modeling system. Bulletin of the American Meteorological Society, 96(12), 2059-2077.

Stephens, SL (1998). Evaluation of Silvicultural Effects and Fuels Treatments on Potential Fire Behavior in Sierra Nevada Mixed-Conifer Forests. Forest Ecology and Management, 105 (1-3): 21-35.

Stephens, SL and Moghaddas, JJ (2005a). Silvicultural and Reserve Impacts on Potential Fire Behavior and Forest Conservation: Twenty-Five Years of Experience from Sierra Nevada Mixed Conifer Forests. Biological Conservation, 125 (3): 369-379.

Stephens, SL and Moghaddas, JJ (2005b). Experimental Fuel Treatment Effects on Forest Structure, Potential Fire Behavior, and Predicted Tree Mortality in a California Mixed Conifer Forest. Forest Ecology and Management, 215 (1-3): 21-36.

Stephens, SL and Moghaddas, JJ (2005c). Fuel Treatment Effects on Woody Debris Snags and Coarse in a Sierra Nevada Mixed Conifer Forest. Forest Ecology and Management, 214 (1-3): 53-64.

Stephens, SL, Meixner, T., Poth, M., McGurk, B., Payne, D. (2004). Prescribed Fire, Soils, and Stream Water Chemistry in a Watershed in the Lake Tahoe Basin, California. International Journal of Wildland Fire, 13 (1): 27-35.

Stocks, B.J. 1980. Black spruce fuel weights in northern Ontario. *Can. J. For. Res.* 10: 498–501.

Stocks, B.J., Alexander, M.E., Wotton, B.M., Stefner, C.N., Flannigan, M.D., Taylor, S.W., Lavoie, N., Mason, J.A., Hartley, G.R., Maffey, M. E., Dalrymple, G. N., Blake, T. W., Cruz, M.G. and Lanoville, R.A. 2004. Crown fire behaviour in a northern jack pine black spruce forest. *Can. J. For. Res.* 34:1548–1560.

Stratton, R.D. Assessing the effectiveness of landscape fuel treatments on fire growth and behavior. Journal of Forestry, 2004, 102(7), 32-40.

Stratton, R.D. Guidance on spatial wildland fire analysis: models, tools, and techniques: United States Department of Agriculture, Forest Service, Rocky Mountain Research Station; General Technical Report RMRS-GTR-183. 2006.

StreetWise 2023. StreetWise CADlink Tablet MDT/MDC. Available online: https://www.streetwisecadlink.com/products/tablet-mdt. (Access 12.09.2023)

Suarez, D., Gomez, C., Medaglia, A., Akhavan-Tabatabaei, R. A Stochastic Programming Approach for Wildfire Suppression: Pre-positioning and Distribution of Resources Under Uncertainty. Ph.D. Thesis, Universidad de los Andes, Bogotá, Colombia, 2016.

Sullivan K., Colleti M., Luke S., (2010) GeoMason, GeoSpatial Support for MASON, *GMU-CS-TR-2010-16, George Mason University* https://cs.gmu.edu/~eclab/projects/mason/extensions/geomason/

Sullivan, A.L. Inside the Inferno: Fundamental Processes of Wildland Fire Behaviour Part 1: Combustion Chemistry and Heat Release. In Fire Sci. Manag., 2017, 3:132–149.

Sullivan, A.L. Inside the Inferno: Fundamental Processes of Wildland Fire Behaviour Part 2: Heat Transfer and Interactions. In Fire Sci. Manag., 2017, 3:150–171.

Sun HG, Zhang JG, Duan AG, He CY (2007) A review of stand basal area growth models. *Forestry studies in China* 9:85–94.

Suryabhagavan K, Alemu M, Balakrishnan M (2016) GIS-based multi-criteria decision analysis for forest fire susceptibility mapping: a case study in Harenna forest, southwestern Ethiopia. *Trop Ecol* 57:33–43.

Svennerberg, G. (2010). Beginning google maps API 3. Apress. https://developers.google.com/maps

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern California landscape. Int J Wildland Fire 17:602–613.

Syvitski, J. P. M., Peckham, S. D., Hilberman, R., & Mulder, T. (2003). Predicting the terrestrial flux of sediment to the global ocean: a planetary perspective. Sedimentary Geology, 162(1–2), 5–24. https://doi.org/10.1016/S0037-0738(03)00232-X

Syvitski, J.P.M. and Milliman, J.D., (2007), Geology, geography and humans battle for dominance over the delivery of sediment to the coastal ocean. J. Geology, 115, 1–19

Syvitski, J.P.M. and Morehead, M.D. (1999) Estimating River-Sediment Discharge to the Ocean: Application to the Eel Margin, Northern California. Marine Geology, 154, 13-28. https://doi.org/10.1016/S0025-3227(98)00100-5

Syvitski, J.P.M., et al., (2003). Predicting the terrestrial flux of sediment to the global ocean: a planetary perspective. Sedimentary Geology, 162, 5–24.

TECHNOSYLVA. 2023. fiResponse™. Available online: https://technosylva.com/products/firesponse/. (Access 13.03.2023)

TECHNOSYLVA. 2023a. Wildfire Analyst™. Available online: https://technosylva.com/products/wildfire-analyst/. (Accessed 14.10.2023)

TECHNOSYLVA. 2023b. FireSim. Available online: https://technosylva.com/products/wildfire-analyst/firesim/. (Accessed 14.10.2023)

Telak, L. J., Dugan, I., and Bogunovic, I. (2021). Soil management and slope impacts on soil properties, hydrological response, and erosion in hazelnut orchard. Soil Syst. 5:5. doi: 10.3390/soilsystems5010005

Tesfahunegn, G. B., Ayuk, E. T., and Adiku, S. G. K. (2021). Farmers' perception on soil erosion in Ghana: Implication for developing sustainable soil management strategy. PLoS One 16:e0242444. doi: 10.1371/journal.pone.0242444

Theodoropoulos, K., Eleftheriadou, E., Grigoriadis, N. (2002). Evolution of the Experimental Surface Surveyor in Pinus (Pinus Halepensis Miller) Forest in Kassandra, Halkidiki, 5 Years After Removal by Mechanical Means. Geotechnical Scientific Issues, 3 (II-3): 12-21.

Thomas, P.H. The size of flames from natural fires. In Symposium (International) on Combustion, 1963, 9(1):844-859.

Thompson, I.D., Okabe, K., Parrotta, J.A., Brockerhoff, E., Jactel, H., Forrester, D.I., Taki, H. Biodiversity and ecosystem services: Lessons from nature to improve management of planted forests for REDD-plus. In Biodivers. Conserv., 2014, 23:2613–2635.

Thompson, M.P., Bowden, P., Brough, A., Scott, J.H., Gilbertson-Day, J., Taylor, A., Anderson, J., Haas, J.R. Application of wildfire risk assessment results to wildfire response planning in the Southern Sierra Nevada, California, USA. In Forests, 2016, 7:64.

Thwaites, T. (2015). The computer program that saved a town. Available online: https://pursuit.unimelb.edu.au/articles/the-computer-program-that-saved-a-town

Tiedemann, AR, O. Klemmedson, J., Bull, EL (2000). Solution to Forest Health Problems with Prescribed Fire: Are Forest Productivity and Wildlife at Risk? Forest Ecology and Management, 127 (1-3): 1-18.

Tolhurst, K., Shields, B., Chong, D. (2008). Phoenix: Development and Application of a Bushfire Risk Management Tool. In Aust. J. Emerg. Manag., 23: 47–54.

Tolk, A. (2015). Learning something right from models that are wrong – epistemology of simulation. Concepts and Methodologies in Modeling and Simulation, Springer–Verlag (2015), pp. 87-106.

Torrano, L. and Valderrabano, J. (2005). Grazing Ability of European Black Pine Understorey Vegetation by Goats. Small Ruminant Research, 58 (3): 253-263.

Tóth, S.F., McDill, M.E., Könnyu, N., George, S. (2013). Testing the use of lazy constraints in solving area-based adjacency formulations of harvest scheduling models. In For. Sci., 59:157-176. doi: 10.5849/forsci.11-040.

Trasobares A., Tomé M., Miina J. (2004). Growth and yield model for *Pinus halepensis* Mill in Catalonia, north-east Spain. *For Ecol Manag* 203:49–62.

Trotsiuk, V., Hartig, F., & Forrester, D. I. (2020). R3PG – An R package for simulating forest growth using the 3-PG process-based model. Methods in Ecology and Evolution, 11(11), 1470–1475.

Tsesmelis, D. E., Karavitis, C. A., Kalogeropoulos, K., Zervas, E., Vasilakou, C. G., Skondras, N. A., et al. (2022). Evaluating the degradation of natural resources in the Mediterranean environment using the water and land resources degradation index, the case of Crete Island. Atmos. 13:135. doi: 10.3390/atmos13010135.

Tuama, Reem & Al-Khaqani, Ebtihal. (2020). Desertification Detection by NDVI and Other Indices: A Case Study in Najaf. Xi'an Dianzi Keji Daxue Xuebao/Journal of Xidian University. 14. 1148-1161. 10.37896/jxu14.9/126.

TUZVO. 2023. SIBYLA – Popis modelu. Available online: https://etools.tuzvo.sk/sibyla/english/. (Access 21.07.2023)

Twery, M.J., Knopp, P.D., Thomasma, S.A., Rauscher, H.M., Nute, D.E., Potter, W.D., Maier, F., Wang, J., Dass, M., Uchiyama, H., Glende, A., Hoffman, R.E. NED-2: A decision support system for integrated forest ecosystem management. In Computers and Electronics in Agriculture, 2005, 49:24-43.

Tymstra, C., Bryce, R.W., Wotton, B.M., Taylor, S.W. Armitage, O.B. Development and Structure of Prometheus: The Canadian Wildland Fire Growth Simulation Model. Natural Resources Canada: Edmonton, AL, Canada, 2010.

Tymstra, C., Bryce, R.W., Wotton, B.M., Taylor, S.W., Armitage, O.B. Development and Structure of Prometheus: the Canadian Wildland Fire Growth Simulation Model. Nat. Resour. Can., Can. For. Serv., North. For. Cent., Edmonton, Alberta. Inf. Rep. NOR-X-417, 2010, 88 p.

Tymstra, C., Bryce, R.W., Wotton, B.M., Taylor, S.W., Armitage, O.B. Development and Structure of Prometheus: the Canadian Wildland Fire Growth Simulation Model. Nat. Resour. Can., Can. For. Serv., North. For. Cent., Edmonton, Alberta. Inf. Rep. NOR-X-417, 2010, 88 p.

U.S. EPA. Comparative Assessment of the Impacts of Prescribed Fire Versus Wildfire (CAIF): A Case Study in the Western U.S. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-21/197, 2021.

Úbeda, X., Sarricolea, P. Wildfires in Chile: A review. In Glob. Planet. Chang., 2016, 146: 152–161.

UNCCD, (1994). Elaboration of an international convention to combat desertification in countries experiencing serious drought and/or desertification, particularly in Africa. General Assembly, United Nations, 1–58 pp.

United States Department of Agriculture (2023). First Order Fire Effects Model (FOFEM). https://www.fs.usda.gov/ccrc/tool/first-order-fire-effects-model-fofem

[35] United States Department of Agriculture (2023). Fuel and Fire Tools (FFT). https://www.fs.usda.gov/ccrc/tool/fuel-and-fire-tools-fft

University of Washington (2023). Fuel & Fire Tools (FFT). https://depts.washington.edu/fft/

Urbanski, S. (2014). Wildland fire emissions, carbon, and climate: Emission factors. Forest Ecology and Management, 317, 51-60.

US Forest Service. 2023. Forest Vegetation Simulator (FVS). Available online: https://www.fs.usda.gov/fvs/index.shtml. (Access 14.09.2023)

Vacchiano, G. and Ascoli, D. 2015. An implementation of the Rothermel fire spread model in the R programming language. Fire Technology 51:523 - 535.

Vacik H., Lexer, M.J., Rammer, W., Seidl, R., Hochbichler, E., Strauss, M., Schachinger, C. ClimChAlp - a web-based decision support system to explore adaptation options for silviculture in secondary Norway spruce forests in Austria. In: Falcao, A., Rosset. C (Eds.) , Proceedings of the Workshop on Decision Support Systems in Sustainable Forest Management. Lisbon, April 2010.

Valderrabano, J. and Torrano, L. (2000). The Potential for Using Goats to Control Genista Scorpius Shrubs in European Black Pine Stands. Forest Ecology and Management, 126 (3): 377-383.

Van Der Merwe, M., Minas, J.P., Ozlen, M., Hearne, J.W. A mixed integer programming approach for asset protection during escaped wildfires. In Can. J. For. Res., 2015, 45:444–451.

Van Oost, K., Govers, G., Desmet, P., (2000). Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. Landsc. Ecol. 15 (6), 577–589.

Van Rompaey, A.J., Verstraeten, G., Van Oost, K., Govers, G., Poesen, J., (2001). Modelling mean annual sediment yield using a distributed approach. Earth Surf. Process. Landf. 26 (11), 1221–1236.

Van Wagner CE, Pickett TL (1985) Equations and FORTRAN Program for the Canadian Forest Fire Weather Index System, Ottawa, ON, Can For Serv Tech Rep 33.

Van Wagner, C.E. 1977. Conditions for the start and spread of crown fire. *Can. J. For. Res.* 7: 23–34.

Van Wagner, C.E. Conditions for the start and spread of crown fire. Canadian Journal of Forest Research, 1977, 7(1):23-34.

Van Wagner, C.E. Conditions for the start and spread of crown fire. Can. J. For. Res., 1977, 7(1):23-34.

Van Wagner, C.E. Prediction of crown fire behavior in conifer stands. In '10th Conference of Fire and Forest Meteorology', 17–21 April 1989, Ottawa, ON, Canada. (Eds DC MacIver, H Auld, R Whitewood), 1989, pp. 207–212.

Van Wagner, C.E. Prediction of crown fire behavior in two stands of jack pine. In Canadian Journal of Forest Research, 1993, 23: 442–449.

Varol, M. (2011). Assessment of heavy metal contamination in sediments of the Tigris River (Turkey) using pollution indices and multivariate statistical techniques. *Journal of Hazardous Materials*, *195*, 355–364. https://doi.org/10.1016/J.JHAZMAT.2011.08.051

Vasconcelos, M., Guertin, D. FIREMAP—Simulation of fire growth with a geographic information system. In Int. J. Wildland Fire, 1992, 2(2):87–96.

Vasconcelos, M.J., Guertin, D.F. FIREMAP - simulation of fire growth with a geographic information system. In International Journal of Wildland Fire, 1992, 2(2):87-96.

Vasilakos C, Kalabokidis K, Hatzopoulos J, Matsinos J (2008) Identifying wildland fire ignition factors through sensitivity analysis of a neural network. Nat Hazards 50:125–143.

Vasiliev, D. (2022). The Role of Biodiversity in Ecosystem Resilience. *IOP Conference Series: Earth and Environmental Science*, *1072*(1). https://doi.org/10.1088/1755-1315/1072/1/012012

Veeraswamy et al., https://gala.gre.ac.uk/id/eprint/18045/1/18045%20GALEA_Simulation_of_Urban-Scal_%20Evacuation_Scenarios_2017.pdf

Verbeeck, H., Samson, R., Granier, A., Montpied, P., & Lemeur, R. (2008). Multi-year model analysis of GPP in a temperate beech forest in France. Ecological Modelling, 210(1), 85–103.

Verde, J., Zêzere, J. Assessment and validation of wildfire susceptibility and hazard in Portugal. In Nat. Hazards Earth Syst. Sci., 2010, 10:485–497.

Verkerk P.J., Schelhaas M.J., Immonen V., Hengeveld G., Kiljunen J., Lindner M., Nabuurs G.J., Suominen T., Zudin S. (2018). Manual for the European Forest Information Scenario model (EFISCEN 4.1). European Forest Institute Technical Report 99: 1-110.

Vieira, G.C., de Mendonça, A.R., da Silva, G.F., Zanetti, S.S., da Silva, M.M, dos Santos, A.R. Prognoses of diameter and height of trees of eucalyptus using artificial intelligence. In Science of The Total Environment, 2018, 619–620:1473-1481. doi: 10.1016/j.scitotenv.2017.11.138.

Vospernik S (2021) Basal area increment models accounting for climate and mixture for Austrian tree species. *For Ecol Manage* 480:118725.

Wahlqvist, J., Ronchi, E., Gwynne, S. M., Kinateder, M., Rein, G., Mitchell, H., ... & Kuligowski, E. (2021). The simulation of wildland-urban interface fire evacuation: The WUI-NITY platform. *Safety science*, *136*, 105145.

Wang Y, Anderson KR. (2010) An evaluation of spatial and temporal patterns of lightning- and human-caused forest fires in Alberta, Canada, 1980–2007. Int J Wildland Fire 19:1059–1072.

Wang, L., Wu, P., Chu, F. A Multi-objective Emergency Scheduling Model for Forest Fires with Priority Areas. In Proceedings of the 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 14–17 December 2020, IEEE: Piscataway, NJ, USA, 2020, pp. 610–614.

Wang, Z., & Zlatanova, S. (2019). Safe route determination for first responders in the presence of moving obstacles. *IEEE transactions on intelligent transportation systems*, *21*(3), 1044-1053.

Wang, Z., Zlatanova, S., Moreno, A., Van Oosterom, P., & Toro, C. (2014). A data model for route planning in the case of forest fires. *Computers & Geosciences*, *68*, 1-10.

Webb, R.H., Griffiths, P.G., (2001). Sediment delivery by ungauged tributaries of the Colorado River in Grand Canyon. Tucson, AZ: USGS, Fact Sheet 018-01.

Wei, Y., Belval, E.J., Thompson, M.P., Calkin, D.E., Stonesifer, C.S. A simulation and optimisation procedure to model daily suppression resource transfers during a fire season in Colorado. In Int. J. Wildland Fire, 2016, 26:630–641.

Wei, Y., Bevers, M., Belval, E., Bird, B. A chance-constrained programming model to allocate wildfire initial attack resources for a fire season. In For. Sci., 2015, 61:278–288.

Wei, Y., Bevers, M., Belval, E.J. Designing seasonal initial attack resource deployment and dispatch rules using a two-stage stochastic programming procedure. In For. Sci., 2015, 61:1021–1032.

Wei, Y., Hoganson, H.M. Scheduling forest core area production using mixed integer programming. In Can. J. For. Res., 2007, 37(10):1924-1932. doi: 10.1139/X07-033.

Wei, Y., Rideout, D.B., Hall, T.B. Toward Efficient Management of Large Fires: A Mixed Integer Programming Model and Two Iterative Approaches. In For. Sci., 2011, 57:435–447.

Wei, Y., Thompson, M.P., Belval, E., Gannon, B., Calkin, D.E., O'Connor, C.D. Comparing contingency fire containment strategies using simulated random scenarios. In Nat. Resour. Model., 2021, 34:e12295.

Wei, Y., Thompson, M.P., Haas, J.R., Dillon, G.K., O'Connor, C.D., O'Connor, C.D. Spatial optimization of operationally relevant large fire confine and point protection strategies: Model development and test cases. In Can. J. For. Res., 2018, 48:480–493.

Wei, Y., Thompson, M.P., Scott, J.H., O'Connor, C.D., Dunn, C.J. Designing operationally relevant daily large fire containment strategies using risk assessment results. In Forests, 2019, 10:311.

Weifeng Wang, Changhui Peng, S.Y. Zhang, Xiaolu Zhou, Guy R. Larocque, Daniel D. Kneeshaw, Xiangdong Lei. (2011). Development of TRIPLEX-Management model for simulating the response of forest growth to pre-commercial thinning. Ecological Modelling, Volume 222, Issue 14, Pages 2249-2261.

Werth, P.A., Potter, B.E., Clements, C.B., Finney, M.A., Goodrick, S.L., Alexander, M.E., Cruz, M.G., Forthofer, J.A., McAllister, S.S. Synthesis of knowledge of extreme fire behavior: volume I for fire managers. Portland, OR: USDA Forest Service, Pacific Northwest Research Station, General Technical Report PNW-GTR-854, 2011.

WFAS. 2023. WFAS. Available online: https://www.wfas.net/index.php?option=com_content&view=article&id=74&Itemid=476. (Access 20.08.2023)

WFDSS. 2023. Wildland Fire Decision Support System. Available online: https://wfdss.usgs.gov/wfdss/WFDSS_Home.shtml. (Access 12.09.2023)

Wheater, H.S., Jakeman, A.J., Beven, K.J., (1993). Progress and directions in rainfall-runoff modelling. In: Jakeman, A.J., Beck, M.B., McAleer, M.J. (Eds.), Modelling Change in Environmental Systems. John Wiley and Sons, Chichester, pp. 101–132.

Wheater, H.S.; Jakeman, A.J.; Beven, K.J. Progress and Directions in Rainfall-Runoff Modelling; FAO: Rome, Italy, 1993.

Wikipedia.org. 2023. Google Earth. Available online: https://en.wikipedia.org/wiki/Google_Earth. (Access 10.09.2023.

Wikström, P., L. Edenius, Elfving, B., Eriksson, L.O., Lämås, T., Sonesson, J., Öhman, K., Wallerman, J., Waller, C., Klintebäck, F. 2011. The Heureka forestry decision support system: An overview. In Mathematical and Computational Forestry & Natural-Resource Sciences, 2011, 3(2):87-94.

Wildland Fire Decision Support System. 2023. Wildland Fire Decision Support System. Available online: https://wfdss.usgs.gov/wfdss/WFDSS_Home.shtml. (Access 21.08.2023)

Williams, J.R., (1975). Sediment-Yield Prediction with Universal Equation Using Runoff Energy Factor. In: Proceedings of the sediment yield workshop: "Present and prospective technology for predicting sediment yield and sources". USDA-ARS, 28–30 November, Washington, DC, 244–252.

Williams, J.R., Nicks, A.D. and Arnold, J.G., (1985). Simulator for Water Resources in Rural Basins. Journal of Hydraulic Engineering, 111:6, pp. 970-986.

Wischmeier, W.H. and Smith, D.D., (1978). Predicting Rainfall Erosion Losses, A guide to conservation planning. Washington, DC: USDA-ARS (Agriculture Handbook 537), 58.

WISE. 2018. Wildfire Safety Evaluator. Available online: https://wise.wildfireanalyst.com/#safety-zones. (Access 11.08.2022)

Wu, P., Cheng, J., Feng, C. Resource-Constrained Emergency Scheduling for Forest Fires with Priority Areas: An Efficient Integer-Programming Approach. In IEEJ Trans. Electr. Electron. Eng., 2019, 14: 261–270.

Wu, Z., Lei, S., Bian, Z. et al. Study of the desertification index based on the albedo-MSAVI feature space for semi-arid steppe region. Environ Earth Sci 78, 232 (2019). https://doi.org/10.1007/s12665-019-8111-9.

Xenakis, G., Ray, D., & Mencuccini, M. (2008). Sensitivity and uncertainty analysis from a coupled 3-PG and soil organic matter decomposition model. Ecological Modelling, 219(1), Article 1.

Xu, X.; Liu, L.; Han, P.; Gong, X.; Zhang, Q. Accuracy of Vegetation Indices in Assessing Different Grades of Grassland Desertification from UAV. Int. J. Environ. Res. Public Health 2022, 19, 16793. https://doi.org/10.3390/ijerph192416793.

Yang X, Jin X, Zhou,Y (2021) Wildfire risk assessment and zoning by integrating Maxent and GIS in Hunan Province, China. *Forests* 12:1299.

Yang, Q., Liu, G., Casazza, M., Gonella, F., Yang, Z. Three dimensions of biodiversity: New perspectives and methods. In Ecological Indicators, 2021, 130:108099. doi: 10.1016/j.ecolind.2021.108099.

Yang, Z., Guo, L., Yang, Z. Emergency logistics for wildfire suppression based on forecasted disaster evolution. In Ann. Oper. Res., 2019, 283:917–937

Ye J, Wu M, Deng Z, Xu S, Zhou R, Clarke KC (2017) Modeling the spatial patterns of human wildfire ignition in Yunnan province, China. Appl Geogr 89:150-162.

Yin HW, Kong FH, Li XZ (2004) RS and GIS-based forest fire risk zone mapping in da Hinggan mountains. *Chin Geogr Sci* 14:251–257.

Yohan, L., Byungdoo, L., Kyung, H.K. Optimal spatial allocation of initial attack resources for firefighting in the Republic of Korea using a scenario optimization model. In J. Mt. Sci. 2014, 11:323–335.

Young R.A., C.A. Onstad, D.D. Bosch, W.P. Anderson. (1994). Agricultural Non-Point Source Pollution Model, Version 4.03 - AGNPS User's Guide.

Young, R.A., Onstad, C.A., Bosch, D.D., Anderson, W.P., (1987). AGNPS, agricultural nonpoint source pollution. A watershed analysis tool. In: Conservation Research Report 35. US Department of Agriculture, Washington, DC

Young, R.A., Onstad, C.A., Bosch, D.D., Anderson, W.P., (1989). AGNPS: A nonpoint-source pollution model for evaluating agricultural watersheds. J. Soil Water Conserv. 44, 121–13.

Zabowski, D., Java, B., Scherer, G., Everett, R. L., Ottmar, R. (2000). Timber Harvesting Residue Treatment: Part I. Responses of Conifer Seedlings, Soils and Microclimate. Forest Ecology and Management, 126 (1): 25-34.

Zárate, L., Arnaldos, J., Casal, J. Establishing safety distances for wildland fires. In Fire Safety Journal, 2008, 43(8):565-575.

Zarris, D., Lykoudi, E., and Koutsoyiannis, D., (2002). Sediment yield estimation from a hydrographie survey: A case study for the Kremasta reservoir basin, Greece, Proc. of the 5th International Conference "Water Resources Management in the Era of Transition", Athens, 4-8 September, 338-345pp.

Zarris, D., Lykoudi, E., Panagoulia, D., (2007). Sediment yield estimates in North-Western Greece and analyses with hydrologic and geomorphologic factors. In: Proceedings of the 11th International Congress of the Geological Society of Greece, 24−26 May, Athens Greece, Vol. XXXVII, 629−640.

Zeferino, J.A. Optimizing the location of aerial resources to combat wildfires: A case study of Portugal. In Nat. Hazards, 2020, 100:1195–1213.

Zhang JG, Duan AG (2004) Study on Theoretical Growth Equation and Diameter Structure Model. Beijing: Life Science Press, 2–7.

Zhang ZX, Zhang HY, Zhou DW (2009) Using GIS spatial analysis and logistic regression to predict the probabilities of human-caused grassland fires. J Arid Environ 74:386–393.

Živojinović, I., Weiss, G., Lidestav, G., Feliciano, D., Hujala, T., Dobšinská, Z., Lawrence, A., Nybakk, E., Quiroga, S., Schraml, U. Forest Land Ownership Change in Europe. Cost Action FP120 FACEMAP Country Reports; University of Natural Resources and Life Sciencesn (BOKU): Vienna, Austria, 2015.

Zouhar, K. Polystichum munitum. In: Fire Effects Information System, [Online]. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory (Producer), 2015. Available online: www.fs.usda.gov/database/feis/plants/fern/polmun/all.html (Access 23.09.2023).

Zylstra, P.J. Flammability dynamics in the Australian Alps. In Austral Ecol., 2018, 43:578–591.

5. Appendix – Summary assessments of forest models and tools

This chapter serves as an appendix that gathers and lists the assessments of models and tools that have been surveyed and reviewed in chapter 2.

5.1 Context and approach

The assessment of existing and tools is meant to help prospective researchers and developers to find forest models and tools that are suitable for them, according to certain criteria. These assessments have been carried out having in mind especially the needs of stakeholders within the SILVANUS project, although they could also be use in other projects, research studies or contexts. The methodology employed relied on the following steps:

- Consensus on the set of criteria to be used for the assessment of models and tools.
- Definition of two specific templates, one that can be used for the assessment of forest models (given in Table 43) and one applicable for the assessment of tools (given in Table 44).
- Assessment by the partner that was assigned as lead contributor in each model and tool contributor. The assessment typically and mostly relied on information that can be found in literature sources and on the internet, while personal past experience working with the models and tools was also employed, when such past experience existed and was applicable.
- Review by a second partner that played the role of reviewer for that particular category of models and tools.

Reflecting on this methodology, it is worth highlighting the following as a disclaimer:

- The assessments certainly contain a subjective element and should, thus, be treated only as indicative before being used for the final decision making. The decision maker should always consult multiple sources and experts, as well as reflect on the actual needs and priorities of the project at hand.
- The assessments were made in the context of the SILVANUS project, so the original goal has been to serve the needs of technology development partners and other stakeholders in this specific project. This does not preclude that they might also be found useful and valuable in other projects or contexts, however certain caution should be exercised.
- The scores assigned are by no means a measure of the scientific value of a model or tool. All models and tools reviewed and documented are of high scientific value and significance. The scores merely served as a structured approach for making more informed decisions in the context of the SILVANUS project, with respect to selecting models and tools that could be integrated, already or in the future, in the SILVANUS framework with the resources available to the project. Hence, the goal was to limit as much as possible any arbitrary or random decisions, whenever such decisions would have to be taken.
- There is no one-size-fits-all approach. This means that certain models and tools could not be assessed, e.g. due to lack of sufficient information or knowledge, or simply because such an assessment would not be useful or reliable, or would not even make sense (e.g., if models of a particular are usable under different circumstances, so that they are not directly comparable).

Table 43: Template table for the assessment of forest models. The same legend and notes apply to all model assessments that have been carried out.

Model Assessment (template)									
Model Code	**Suitability and Completeness**	**Weight**	**Prediction Capacity**	**Weight**	**Data Requirements**	**Weight**	**Easy to implement as S/W**	**Weight**	**Total Score**

Model Assessment (template)										
Model Code	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score

Legend and notes:

Suitability and Completeness: Degree to which the model provides functions that meet user needs (when used under specified conditions), as well as degree to which the set of functions covers all user objectives in specific operational scenarios. Include a single integer score from 0 to 10. Convention: Excellent (8-10); Satisfactory (6-8); Moderate (4-6); Inadequate (2-4); Unacceptable (0-2).

Prediction Capacity: The prediction capacity (e.g. relevance, accuracy, or other suitable metric) as a percentage from 0 to 100% (the higher the better).

Data Requirements: An assessment of the data requirements of the model. Higher data requirements (more data or more parameters) should yield lower scores. Convention - Data requirements are: Few and very realistic (8-10); Moderate but generally realistic (6-8); Many but could be achieved under certain conditions (4-6); Very high (2-4); Extremely high (unrealistic) (0-2).

Easy to implement as S/W: How easy it will be to implement the model as a S/W tool or component within the SILVANUS Platform: Easy and straightforward (8-10); Achievable but with some difficulties (6-8); Hard but could be achieved with sufficient resources (4-6); Very hard (2-4); Extremely hard (unrealistic) (0-2).

Table 44: Template table for the assessment of tools. The same legend and notes apply to all tool assessments that have been carried out.

Tool Assessment (template)									
Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score

Legend and notes:

Functional Suitability and Completeness: Degree to which the S/W product or tool provides functions that meet user needs (when used under specified conditions), as well as degree to which the set of functions covers all user objectives in specific operational scenarios. Include a single integer score from 0 to 10. Convention: Excellent (8-10); Satisfactory (6-8); Moderate (4-6); Inadequate (2-4); Unacceptable (0-2).

Functional Correctness: To what extent the outcomes of the S/W product or tool can be considered as correct and precise? An average value from the evidence that exists in literature resources. Convention: Excellent (8-10); Satisfactory (6-8); Moderate (4-6); Inadequate (2-4); Unacceptable (0-2).

Compatibility and Interoperability: Degree to which the S/W product or tool can exchange information with other products, systems or components, and/or perform its required functions while sharing the same H/W or S/W environment. Degree to which a tool can perform its required functions efficiently, exchange information and use the information while sharing a common environment and resources with other products, without detrimental impact on any other product. A. single integer score from 0 to 10. Convention: Excellent (8-10); Satisfactory (6-8); Moderate (4-6); Inadequate (2-4); Unacceptable (0-2).

License Type and IPR: How open or restrictive the IPR or license type of the tool are. Convention: Open (any restrictions are insignificant) (8-10); Few restrictions (6-8); Important restrictions (4-6); Very important restrictions (2-4); Closed or proprietary, with several and severe limitations (0-2).

5.2 Assessment of models and tools related to strategies or methodologies for resource deployment and management to mitigate forest wildfires

Table 45 provides a summary assessment of selected models related to strategies or methodologies for resource deployment and management to mitigate forest wildfires. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 45: Assessment of models related to strategies or methodologies for resource deployment and management to mitigate forest wildfires.

Model Code	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score
M11.1	10	0.25	7	0.25	8	0.25	7	0.25	16
M11.7	10	0.25	10	0.25	10	0.25	0	0.25	20
M11.8	10	0.25	10	0.25	10	0.25	0	0.25	20
M11.9	10	0.25	10	0.25	10	0.25	0	0.25	20
M11.12	8	0.25	8	0.25	8	0.25	6	0.25	17
M11.13	8	0.25	8	0.25	8	0.25	6	0.25	17
M11.14	6	0.25	7	0.25	10	0.25	10	0.25	16

Table 46 provides a summary assessment of existing tools used for resource deployment and management to mitigate forest wildfires.

Table 46: Assessment of tools used for resource deployment and management to mitigate forest wildfires.

Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score
T11.1	10	0.25	10	0.25	8	0.25	2	0.25	20
T11.2	10	0.25	10	0.25	10	0.25	0	0.25	20
T11.3	10	0.25	10	0.25	10	0.25	2	0.25	20
T11.4	10	0.25	10	0.25	10	0.25	0	0.25	20
T11.5	10	0.25	10	0.25	10	0.25	8	0.25	21
T11.6	10	0.25	10	0.25	8	0.25	2	0.25	20
T11.7	10	0.25	9	0.25	10	0.25	2	0.25	20
T11.8	10	0.25	10	0.25	6	0.25	0	0.25	19
T11.9	10	0.25	10	0.25	10	0.25	10	0.25	22
T11.10	10	0.25	10	0.25	8	0.25	2	0.25	20
T11.11	8	0.25	8	0.25	8	0.25	10	0.25	17

5.3 Assessment of fire behavior models and tools

Table 47 provides a summary assessment of selected fire behavior models. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 47: Assessment of fire behavior models.

Model Code	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score
M21.1	10	0.25	9	0.25	5	0.25	4	0.25	18
M21.21	6	0.25	9	0.25	3	0.25	4	0.25	17
M21.22	8	0.25	9	0.25	3	0.25	2	0.25	17
M21.23	6	0.25	8	0.25	6	0.25	8	0.25	16
M21.24	10	0.25	8	0.25	4	0.25	4	0.25	16

Table 48 provides a summary assessment of tools employed for fire behavior analysis. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 48: Assessment of tools used for fire behavior analysis.

Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score
T21.19	6	0.25	8	0.25	5	0.25	10	0.25	17
T21.20	8	0.25	8	0.25	8	0.25	2	0.25	16
T21.21	10	0.25	8	0.25	8	0.25	2	0.25	17
T21.22	6	0.25	6	0.25	6	0.25	2	0.25	12
T21.23	8	0.25	8	0.25	8	0.25	2	0.25	16
T21.24	6	0.25	6	0.25	6	0.25	0	0.25	12
T21.25	8	0.25	8	0.25	10	0.25	10	0.25	18
T21.26	8	0.25	7	0.25	6	0.25	2	0.25	14
T21.27	10	0.25	8	0.25	8	0.25	2	0.25	17
T21.28	10	0.25	8	0.25	8	0.25	2	0.25	17

5.4 Evaluation of models and tools for fire risk assessment

Table 49 provides an evaluation for the majority of the models relevant to fire risk assessment. Furthermore, Table 50 provides an evaluation of the corresponding software tools that implement (calculate) the models. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 49: Assessment of models for fire risk assessment.

Model	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M23.1	4	0.25	3	0.25	8	0.25	9	0.25	6
M23.2	7	0.25	6	0.25	8	0.25	9	0.25	7.5
M23.3	7	0.25	6	0.25	8	0.25	9	0.25	7.5
M23.4	4	0.25	3	0.25	8	0.25	9	0.25	6
M23.5	6	0.25	6	0.25	8	0.25	9	0.25	7.25
M23.6	7	0.25	6	0.25	8	0.25	9	0.25	7.5
M23.7	8.5	0.25	7	0.25	8.5	0.25	8	0.25	8
M23.8	7.5	0.25	6.5	0.25	8	0.25	7	0.25	7.25
M23.9	7	0.25	6	0.25	8	0.25	9	0.25	7.5
M23.10	9	0.25	7	0.25	8.5	0.25	provides	0.25	8.25
M23.11	6.5	0.25	7	0.25	8	0.25	8	0.25	7.38
M23.12	7.5	0.25	7.5	0.25	7	0.25	9	0.25	7.75
M23.13	6	0.25	6	0.25	7	0.25	8	0.25	6.75
M23.14	5	0.25	6.5	0.25	7	0.25	7	0.25	6.38
M23.15	6.5	0.25	6.5	0.25	6.5	0.25	9	0.25	7.13
M23.16	4	0.25	3	0.25	8	0.25	9	0.25	6
M23.17	9	0.25	9	0.25	8.5	0.25	9	0.25	8.9
M23.18	8.5	0.25	8	0.25	8.5	0.25	9	0.25	8.5
M23.19	7.5	0.25	8.5	0.25	6	0.25	7.5	0.25	7.36
M23.20	9	0.25	8.5	0.25	6	0.25	9	0.25	8.13

Table 50: Assessment of tools for fire risk assessment.

Model	Functional Suitability and Completeness	Weight(1)	Functional Correctness	Weight(2)	Compatibility and Interoperability	Weight(3)	License Type and IPR	Weight(4)	Total Score
T23.1	6	0.25	4	0.25	7	0.25	4	0.25	5.3
T23.2	7	0.25	8	0.25	4	0.25	4	0.25	5.8
T23.3	7	0.25	8	0.25	4	0.25	4	0.25	5.8
T23.4	6	0.25	4	0.25	7	0.25	4	0.25	5.3
T23.5	8	0.25	7.5	0.25	7	0.25	4	0.25	6.6
T23.6	7	0.25	8	0.25	4	0.25	4	0.25	5.8
T23.7	8	0.25	7.5	0.25	7	0.25	10	0.25	8.1
T23.8		0.25		0.25		0.25		0.25	
T23.9	7	0.25	8	0.25	4	0.25	4	0.25	5.8
T23.10	7.5	0.25	7.5	0.25	7	0.25	10	0.25	8.0
T23.11	6.5	0.25	8	0.25	7	0.25	4	0.25	6.4
T23.12	7	0.25	8.5	0.25	7	0.25	4	0.25	6.6
T23.13	7.5	0.25	8.5	0.25	5.5	0.25	4	0.25	6.4
T23.14	6	0.25	9	0.25	5	0.25	4	0.25	6.0

T23.15	8	0.25	8.5	0.25	5	0.25	4	0.25	6.4
T23.16	6	0.25	4	0.25	7	0.25	4	0.25	5.3
T23.17	9	0.25	9.5	0.25	7.5	0.25	10	0.25	9.0
T23.18	9	0.25	8.5	0.25	7	0.25	10	0.25	8.6
T23.19	-	0.25	-	0.25	-	0.25		0.25	-
T23.20	-	0.25	-	0.25	-	0.25		0.25	-

5.5 Assessment of forest growth models

Table 51 provides a summary assessment of forest growth models focused on basal area increment prediction. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 51: Assessment of forest growth models focused on basal area increment prediction.

Model	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M31.1	8	0.25	4	0.25	7	0.25	9	0.25	7.00
M31.2	5	0.25	3	0.25	7	0.25	8	0.25	5.75

Table 52 presents the scores and general assessments of the process-based forest growth models. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 52: Assessment of (process-based) forest growth models.

Name	Suitability and Completeness	Weight (1)	Prediction Capacity	Weight (2)	Data Requirements	Weight (3)	Easy to implement as S/W	Weight (4)	Total Score
3-PG	7	0.25	87.5	0.25	5	0.25	7	0.25	6.94
3-PGmix	9	0.25	89	0.25	5	0.25	7	0.25	7.48
3-PGN-BW	5	0.2	85	0.25	5	0.3	7	0.25	6.38
4C v2.2	7	0.25	87.5	0.25	3	0.25	3	0.25	5.44
ANAFORE	5	0.2	80	0.25	5	0.25	7	0.3	6.35
BIOME-BGC	5	0.2	77.5	0.25	5	0.25	7	0.3	6.29
CABALA	3	0.2	80	0.3	3	0.25	3	0.25	4.50
CASTANEA	5	0.2	80	0.3	5	0.25	7	0.25	6.40
FINNFOR	9	0.25	80	0.25	5	0.25	7	0.25	7.25
FORCLIM	9	0.25	75	0.25	7	0.25	7	0.25	7.63
FOREST-BGC	5	0.2	85	0.3	7	0.25	7	0.25	7.05
FORSPACE	7	0.25	77.5	0.25	7	0.25	7	0.25	7.19
FORUG	3	0.15	80	0.3	5	0.3	7	0.25	6.10
PNET	5	0.2	70	0.3	5	0.25	7	0.25	6.10
SECRETS	7	0.25	77.5	0.25	3	0.25	3	0.25	5.19
TREEDYN3	7	0.25	87.5	0.25	3	0.25	3	0.25	5.44
TRIPLEX	7	0.25	70	0.25	7	0.25	7	0.25	7.00
WOODPAM	3	0.15	87.5	0.3	3	0.25	3	0.3	4.73

CENW	5	0.2	82.5	0.25	3	0.25	3	0.3	4.71
GOTILWA+	5	0.2	77.5	0.25	7	0.25	7	0.3	6.79
ecosys	5	0.2	82.5	0.25	3	0.3	3	0.25	4.71
GO+ v3.0	5	0.2	87.5	0.3	3	0.25	3	0.25	5.13
3D-CMCC-FEM LUE	5	0.2	90	0.25	5	0.3	7	0.25	6.50
3D-CMCC-BGC BGC	5	0.2	92.5	0.25	3	0.3	3	0.25	4.96

5.6 Assessment of models used for estimating the effect of environmental factors on forest susceptibility to fire

Table 53 provides the summary assessment of the two selected models that can be used for estimating the effect of environmental factors on forest susceptibility to fire. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 53: Assessment of models which can be used for estimating the effect of environmental factors on forest susceptibility to fire.

Name	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score
TREEMIG	5	0.15	75	0.3	5	0.25	7	0.3	6.35
CENTURY v4.0	5	0.2	85	0.25	5	0.25	7	0.3	6.48

5.7 Assessment of models for wildfire ignition prediction

Table 54 provides a summary assessment of models that can be used for wildfire ignition prediction. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 54: Assessment of models for wildfire ignition prediction.

Model	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M51.1	7	0.25	6	0.25	8	0.25	9	0.25	7.50
M51.2	5	0.25	6.5	0.25	7	0.25	6	0.25	6.10
M51.3	5	0.25	6	0.25	7	0.25	8	0.25	6.50
M51.4	6	0.25	6	0.25	7.5	0.25	8	0.25	6.89
M51.5	6	0.25	6	0.25	7	0.25	8	0.25	6.75
M51.6	6	0.25	6	0.25	7.5	0.25	8	0.25	6.89
M51.7	6	0.25	6	0.25	7	0.25	8	0.25	6.75
M51.8	5	0.25	5	0.25	7.5	0.25	8.5	0.25	6.50
M51.9	5	0.25	6	0.25	7	0.25	8	0.25	6.50
M51.10	6	0.25	6.5	0.25	7.5	0.25	7	0.25	6.75
M51.11	6	0.25	6.5	0.25	7	0.25	7	0.25	6.63
M51.12	6	0.25	7	0.25	7	0.25	6.5	0.25	6.63
M51.13	6.5	0.25	6.5	0.25	6.5	0.25	9	0.25	7.13

M51.14	5	0.25	6.5	0.25	7	0.25	7	0.25	6.38
M51.15	6	0.25	6.5	0.25	6	0.25	6	0.25	6.13
M51.16	6	0.25	6.5	0.25	7.5	0.25	7	0.25	6.75
M51.17	6.5	0.25	7	0.25	7	0.25	7	0.25	6.88

5.8 Assessment of tools used for calculating biodiversity or for ecological site classification

Table 55 provides a summary assessment of tools used for calculating biodiversity or for ecological site classification. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 55: Assessment of tools used for calculating biodiversity or for ecological site classification.

Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score
T62.1	10	0.25	10	0.25	10	0.25	10	0.25	22
T62.2	9	0.25	9	0.25	8	0.25	7	0.25	19
T62.3	9	0.25	9	0.25	8	0.25	7	0.25	19
T62.4	8	0.25	8	0.25	8	0.25	8	0.25	17
T62.5	10	0.25	8	0.25	9	0.25	6	0.25	17,5
T62.6	10	0.25	8	0.25	8	0.25	6	0.25	17
T62.7	10	0.25	8	0.25	8	0.25	6	0.25	17

5.9 Assessment of models and tools that can be used for the development of forest and landscape management

Table 56 provides a summary assessment of models that can be used for the development of forest and landscape management. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 56: Assessment of models that can be used for the development of forest and landscape management.

Model Code	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score
M63.1	10	0.25	9	0.25	6	0.25	8	0.25	19
M63.2	8	0.25	8	0.25	6	0.25	10	0.25	17
M63.3	10	0.25	9	0.25	5	0.25	8	0.25	19
M63.4	8	0.25	8	0.25	6	0.25	10	0.25	17
M63.5	8	0.25	7	0.25	6	0.25	10	0.25	16
M63.6	9	0.25	9	0.25	6	0.25	10	0.25	19
M63.7	10	0.25	9	0.25	4	0.25	6	0.25	18
M63.8	10	0.25	9	0.25	6	0.25	8	0.25	19

Model Code	Suitability and Completeness	Weight	Prediction Capacity	Weight	Data Requirements	Weight	Easy to implement as S/W	Weight	Total Score
M63.9	8	0.25	8	0.25	6	0.25	8	0.25	17
M63.10	8	0.25	8	0.25	6	0.25	8	0.25	17
M63.11	10	0.25	10	0.25	4	0.25	6	0.25	20
M63.12	8	0.25	7	0.25	8	0.25	6	0.25	15
M63.13	10	0.25	8	0.25	6	0.25	6	0.25	17

Table 57 provides a summary assessment of tools that can be used for the development of forest and landscape management. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 57: Assessment of tools that can be used for the development of forest and landscape management.

Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score
T63.1	8	0.25	8	0.25	8	0.25	10	0.25	18
T63.2	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.3	8	0.25	8	0.25	8	0.25	6	0.25	17
T63.4	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.5	8	0.25	8	0.25	8	0.25	0	0.25	16
T63.6	9	0.25	8	0.25	8	0.25	0	0.25	16
T63.7	8	0.25	8	0.25	8	0.25	0	0.25	16
T63.8	10	0.25	8	0.25	8	0.25	0	0.25	16
T63.9	8	0.25	8	0.25	8	0.25	0	0.25	16
T63.10	8	0.25	8	0.25	8	0.25	0	0.25	16
T63.11	8	0.25	8	0.25	8	0.25	2	0.25	16
T63.12	9	0.25	8	0.25	8	0.25	0	0.25	16
T63.13	9	0.25	8	0.25	8	0.25	6	0.25	17
T63.14	7	0.25	8	0.25	8	0.25	2	0.25	16
T63.15	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.16	8	0.25	8	0.25	8	0.25	6	0.25	17
T63.17	10	0.25	8	0.25	8	0.25	10	0.25	18
T63.18	10	0.25	8	0.25	8	0.25	6	0.25	17

Tool Code	Functional Suitability and Completeness	Weight	Functional Correctness	Weight	Compatibility and Interoperability	Weight	License Type and IPR	Weight	Total Score
T63.19	10	0.25	8	0.25	8	0.25	10	0.25	18
T63.20	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.21	9	0.25	8	0.25	7	0.25	6	0.25	17
T21.22	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.23	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.24	9	0.25	8	0.25	8	0.25	10	0.25	17
T63.25	10	0.25	8	0.25	8	0.25	6	0.25	17
T63.26	10	0.25	8	0.25	7	0.25	6	0.25	17
T63.27	10	0.25	8	0.25	8	0.25	8	0.25	17
T63.28	10	0.25	8	0.25	6	0.25	8	0.25	17

5.10 Assessment of models and tools related to air quality

Table 58 provides a summary assessment of models that are used for estimating smoke dispersion. Table 59 provides a summary assessment of models that are used for estimating emissions. Table 60 provides a summary assessment of popular air quality indexes. Refer to appendix 5.1 for the methodology and limitations of these assessments.

Table 58: Assessment of models for smoke dispersion estimation.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
VALBOX	6	0.25	5	0.25	8	0.25	10	0.25	7.25
VSMOKE	8	0.25	6	0.25	8	0.25	9	0.25	7.75
SASEM	8	0.25	6	0.25	8	0.25	9	0.25	7.75
CALPUFF	9	0.25	7	0.25	7	0.25	7	0.25	7.5
HYSPLIT	9	0.25	8	0.25	7	0.25	7	0.25	7.75
FLEXPART	9	0.25	8	0.25	7	0.25	7	0.25	7.75
Daysmoke	8	0.25	7	0.25	7	0.25	7	0.25	7.25
CMAQ	10	0.25	8	0.25	6	0.25	6	0.25	7.5
WRF-SFIRE	9	0.25	9	0.25	6	0.25	2	0.25	6.5
WFDS	9	0.25	9	0.25	6	0.25	2	0.25	6.5
FIRETEC	9	0.25	9	0.25	6	0.25	2	0.25	6.5

Table 59: Assessment of models for emissions estimation.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
BURNUP	9	0.25	8	0.25	7	0.25	8	0.25	8

CONSUME	9	0.25	8	0.25	7	0.25	8	0.25	8
FEPS/EPM	9	0.25	8	0.25	7	0.25	8	0.25	8
Seiler and Crutzen	9	0.25	6	0.25	9	0.25	10	0.25	8.5

Table 60: Assessment of air quality indexes.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
EAQI	10	0.25	10	0.25	10	0.25	10	0.25	10
AQI	10	0.25	10	0.25	10	0.25	10	0.25	10

Table 61 provides a summary assessment of tools that can be used for the estimation of air quality and corresponding risk for human health. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 61: Assessment of tools related to estimating air quality and corresponding risk for human health.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
FOFEM	8	0.25	9	0.25	9	0.25	9	0.25	8.75
Bluesky	9	0.25	9	0.25	10	0.25	9	0.25	9.25
FuelFireTools	9	0.25	9	0.25	10	0.25	9	0.25	9.25
EFFIS	9	0.25	9	0.25	10	0.25	9	0.25	9.25
CAMS	10	0.25	9	0.25	10	0.25	9	0.25	9.75

5.11 Assessment of models for evacuation route planning and safety zone estimation

The following tables, i.e. Table 62 and Table 63, provide a summary assessment of important models dealing with evacuation route planning and safety zone estimation, respectively. Refer to appendix 5.1 for the methodology and limitations of these assessments.

Table 62: Assessment of selected evacuation route planning models.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M72-EP.1	7	0.25	9	0.25	8	0.25	7	0.25	7.75
M72-EP.2	7	0.25	9.5	0.25	9	0.25	6	0.25	7.875
M72-EP.3	3	0.25	0	0.25	0	0.25	0	0.25	0.75
M72-EP.4	8	0.25	9	0.25	6	0.25	5	0.25	7.00
M72-EP.5	8	0.25	8	0.25	5	0.25	8	0.25	7.25

Table 63: Assessment of safe zone estimation models.

Name	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M72-SZ.1	10	0.25	7	0.25	9	0.25	10	0.25	9.00
M72-SZ.2	10	0.25	5	0.25	10	0.25	10	0.25	8.75

5.12 Assessment of soil erosion models and tools

Table 64 provides a summary assessment of empirical and conceptual soil erosion models (including also geomorphological and topographic models as well as hydraulics models), whereas Table 65 provides a summary assessment of composite soil erosion models. These models have been presented in chapters 2.17-2.19. Refer to appendix 5.1 for the methodology and limitations of these assessments.

Table 64: Assessment of empirical and conceptual soil erosion models.

Model	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
(Generic) models/indices for soil erosion									
M82.2	9	0.25	90%	0.25	7	0.25	8	0.25	8.3
M82.3	8	0.25	80%	0.25	7	0.25	8	0.25	7.8
M82.4	8	0.25	75%	0.25	7	0.25	8	0.25	7.6
M82.1	7	0.25	70%	0.25	7	0.25	8	0.25	7.3
M82.7	7	0.25	65%	0.25	6	0.25	8	0.25	6.9
M82.5	6	0.25	60%	0.25	5	0.25	8	0.25	6.3
M82.6	6	0.25	60%	0.25	5	0.25	8	0.25	6.3
M82.8	5	0.25	55%	0.25	5	0.25	8	0.25	5.9
M82.10	5	0.25	55%	0.25	4	0.25	9	0.25	5.9
M82.9	5	0.25	55%	0.25	3	0.25	9	0.25	5.6
Geomorphological - Topographic models/indices for soil erosion									
M83.6	6	0.25	60%	0.25	5	0.25	8	0.25	6.3
M83.5	5	0.25	55%	0.25	3	0.25	9	0.25	5.6
M83.3	4	0.25	45%	0.25	3	0.25	9	0.25	5.1
M83.1	4	0.25	40%	0.25	3	0.25	9	0.25	5.0
M83. 2	4	0.25	40%	0.25	3	0.25	9	0.25	5.0
M83. 4	4	0.25	40%	0.25	3	0.25	9	0.25	5.0
Hydraulics models/indices for soil erosion									
M84.2	9	0.25	95%	0.25	9	0.25	9	0.25	9.1
M84.1	7	0.25	70%	0.25	6	0.25	8	0.25	7.0

Table 65: Assessment of composite soil erosion models.

Model	Suitability and Completeness	Weight(1)	Prediction Capacity	Weight(2)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
Composite models									
M84CM.8 (IHACRES-WQ)	8	0.25	5	0.25	5	0.25	2	0.25	5.0

M84CM.10 (SWAT)	8	0.25	5	0.25	4	0.25	2	0.25	4.8
M84CM.6 (WEPP)	8	0.25	6	0.25	2	0.25	2	0.25	4.5
M84CM.7 (AGNPS)	8	0.25	5	0.25	2	0.25	2	0.25	4.3
M84CM.1 (ANSWERS)	7	0.25	5	0.25	2	0.25	2	0.25	4.0
M84CM.2 (AGWA)	7	0.25	5	0.25	2	0.25	2	0.25	4.0
M84CM.9 (LISEM)	6	0.25	5	0.25	2	0.25	2	0.25	3.8
M84CM.4 (GUEST)	6	0.25	5	0.25	2	0.25	1	0.25	3.5
M84CM.3 (CREAM)	5	0.25	4	0.25	2	0.25	2	0.25	3.3
M84CM.11 (SWRRB)	4	0.25	5	0.25	2	0.25	2	0.25	3.3
M84CM.5 (EPIC)	4	0.25	5	0.25	2	0.25	1	0.25	3.0

Table 66 provides a summary assessment of selected tools employing empirical and conceptual soil erosion models, whereas Table 67 provides a summary assessment of tools employing composite soil erosion models. Refer to appendix 5.1 for the methodology and limitations of these assessments.

Table 66: Assessment of tools employing empirical and conceptual erosion models.

Model	**Functional suitability and completeness**	**Weight (1)**	**Functional correctness**	**Weight (2)**	**Compatibility and interoperability**	**Weight (3)**	**License type and IPR**	**Weight (4)**	**Total score**
T82.1 (USLE) **Software available FREE:** **GISum-M** http://www2.ufrb.edu.br/gisus-m/ ArcGIS Pro to Estimate Soil https://www.gislounge.com/arcgis-pro-soil-erosion-catchment-basin/	7	0.25	7	0.25	3	0.25	1	0.25	6.3
T82.2 (RUSLE) **Software available:** Soil erosion spatial modeling with RUSLE in ArcGIS software | Udemy Water Erosion (RUSLE2) | Natural Resources Conservation Service (usda.gov)	7	0.25	7	0.25	3	0.25	1	0.25	4.5
T84.1 Daily Based Morgan-Morgan-Finney (DMMF) Soil Erosion Model / https://cran.r-project.org/web/packages/DMMF/DMMF.pdf **Developed in R**	7	0.25	9	0.25	5	0.25	9	0.25	7.5

Table 67: Assessment of tools employing composite models.

Model	Functional suitability and completeness	Weight (1)	Functional correctness	Weight (2)	Compatibility and interoperability	Weight (3)	License type and IPR	Weight (4)	Total score
M84CM.1 (ANSWERS)	-	0.25	-	0.25	-	0.25	-	0.25	0
M84CM.2. (AGWA) **Software available FREE:** Automated Geospatial Watershed Assessment (AGWA) Tool | US EPA	7	0.25	3	0.25	3	0.25	1	0.25	3.5
M84CM.3. (CREAM)	-	0.25	-	0.25	-	0.25	-	0.25	0
M84CM.4. (GUEST)	-	0.25	-	0.25	-	0.25	-	0.25	0
M84CM.5. ((EPIC) **Software available FREE** **Source code available under conditions** Software | EPIC & APEX Models (tamu.edu)	7	0.25	4	0.25	5	0.25	6	0.25	5.5
M84CM.6. (WEPP) **Source code available of relative software WEPP-WQ (Water quality) FREE:** GitHub - ryanpmcg/WEPP-WQ: Water Erosion Prediction Project Water Quality (WEPP-WQ) Model Code	7	0.25	6	0.25	5	0.25	8	0.25	6.5
M84CM.7. (AGNPS) **Available Software FREE:** AGNPS Software Download: USDA ARS	7	0.25	6	0.25	2	0.25	1	0.25	4.0
M84CM.8. (IHACRES-WQ) **Available software FREE:** **IHACRES Rainfall Runoff Model_(Modified Version)** IHACRES Rainfall Runoff Model (Modified Version) - File Exchange - MATLAB Central (mathworks.com)	7	0.25	6	0.25	1	0.25	1	0.25	3.8
M84CM.9. (LISEM) **Available software FREE:** openLISEM - a spatial model for runoff, floods and erosion (utwente.nl) License available: https://www.gnu.org/licenses/old-licenses/gpl-2.0.html#SEC1	8	0.25	9	0.25	3	0.25	8	0.25	7.0
M84CM.10. (SWAT) **Available Software FREE:** SWAT+ | SWAT | Soil & Water Assessment Tool (tamu.edu) Source code available: https://swatplus.gitbook.io/docs/source-code	8	0.25	7	0.25	5	0.25	8	0.25	7.0

M84CM.11. (SWRRB) **Software available FREE:** Software | SWAT | Soil & Water Assessment Tool (tamu.edu)	8	0.25	7	0.25	3	0.25	1	0.25	4.8

5.13 Assessment of soil quality indices

Table 68 provides a summary assessment of soil quality indices. Refer to appendix 5.1 for the methodology and limitations of this assessment.

Table 68: Assessment of soil quality indices.

Model	Suitability and Completeness	Weight(1)	Data Requirements	Weight(3)	Easy to implement as S/W	Weight(4)	Total Score
M85.1	9	0.25	9	0.25	8	0.25	8.7
M85.2	7	0.25	8	0.25	9	0.25	8.0
M85.3	6	0.25	9	0.25	9	0.25	8.0
M85.4	6	0.25	8	0.25	9	0.25	7.7
M85.5	7	0.25	9	0.25	9	0.25	8.3
M85.6	7	0.25	8	0.25	9	0.25	8.0
M85.7	7	0.25	8	0.25	9	0.25	8.0
M85.8	4	0.25	6	0.25	9	0.25	6.3
M85.9	5	0.25	5	0.25	9	0.25	6.3
M85.10	7	0.25	7	0.25	9	0.25	7.7
M85.11	5	0.25	7	0.25	9	0.25	7.0
M85.12	7	0.25	7	0.25	9	0.25	7.7