A Holistic Fire Management Ecosystem for Prevention, Detection and Restoration of Environmental Disasters

TREEADS D.3.1 Report on Ecological and environmental Models of Wildfires

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GLOSSARY OF TERMS

Anthropogenic drivers	Factors affecting a situation, originating from human presence and/or behaviour.
Artificial Neural Networks	A type of computing systems inspired by biological neural networks of animal brains.
Biomass	Plant-based material which constitutes fuel, usually utilized interchangeably with "biofuel".
Bioregion	An ecologically and geographically defined area, smaller than a biogeographic realm, but yet than an ecoregion or an ecosystem.
Buildup Index	The total amount o9f fuel available for combustion.
Burned Area product	A metric containing burning information on a per-pixel basis, concerning remote sensing imaging of areas affected by wildfire.
Continuous Boyce index	A statistical metric quantifying how much a model's predictions differ from random distribution across the prediction gradients.
Discretisation	The process of transferring continuous functions, models, or variables into discrete components.
Drought Code	A numeric quantification of the average moisture content of compact organic layers of high degrees of depth.
Duff Moisture Code	A numeric quantification of the average moisture content of loosely compacted organic layers of moderate degrees of depth.
Ecoregion	An ecologically and geographically defined area, smaller than a bioregion.
Fine Fuel Moisture Code	A numeric quantification of the moisture content of litter and other cured fine fuels.
Fire Hazard Index	A numerical quantification indicating the relative probability of fires starting and spreading.
Fire occurrence prediction model	A model aimed at quantifying the probability of a fire starting at a given area, under specified circumstances.
Fire Risk Index	Fire risk in a particular area due to human presence.

Fire Weather Index	A meteorologically based index used to estimate fire danger.
Forest fire	Any wildfire or prescribed fire that is burning in forested areas, grass, or alpine/tundra vegetation. The main types of forest fire are: ground fire, surface fire, and crown fire.
Forest Fire Behavior Prediction	A system estimating fire area, perimeter, perimeter growth rate, as well as fire behavior at the head, flanks, and back of a wildfire.
Grid cell	A rectangular discretization of the area of interest.
Grid	A rectangularization of the area of interest.
Human-induced ignition risk	The likelihood that human activities, actions, or behaviour will intentionally or unintentionally lead to the ignition of fires.
Initial Spread Index	A combination of wind and the Fine Fuel Moisture Code (FFMC) that represents rate of spread alone without the influence of variable quantities of fuel
Interquartile range	A measure of statistical dispersion, which is the spread of the data.
Land fire hazard map	A geographical representation of areas that are assessed for their susceptibility to wildfires or fire hazards.
location–time dataset	A dataset containing both temporal and spatial information regarding an event.
Logistic regression	A statistical analysis method to predict a binary outcome based on prior observations of a data set.
Multivariate Adaptive Regression Splines	A form of non-parametric regression analysis.
Numerical weather prediction	A method using mathematical models of atmosphere and water bodies to predict the weather, based on current conditions.
Pinus pinaster	A pine tree, native to the south Atlantic Europe region and parts of the western Mediterranean.
Prevention and Preparedness	Prevention involves various measures and strategies to minimize the occurrence of wildfires and preparedness entails planning

	and organizing resources to effectively respond to wildfires when they occur.
Raster GIS	A digital aerial photograph, consisting of a matrix of cells organized into a grid where each cell contains a value representing information, such as temperature, humidity, etc.
Receiver Operating Characteristic	A graphical plot that illustrates the diagnostic ability of a binary classifier, as its discrimination threshold is varied.
Regularisation multiplier	A parameter that adds new constraints to a model, in the form of a penalty.
Remote sensing	The act of acquiring information about an object or phenomenon without making direct physical contact with it.
runoff	The flow of water occurring on the ground surface when excess rain/storm/melt-water can no longer sufficiently rapidly infiltrate in the soil.
Suppression policies	Suppression policies: A set of strategies, guidelines, and actions implemented by fire management and firefighting agencies to control, contain, and extinguish wildfires or forest fires.
Temporal and spatial resolution	Spatial resolution is the amount of spatial detail in an observation; temporal resolution is the amount of temporal detail in an observation.
Wildfire	An unplanned or unwanted natural or human-caused fire, as contrasted with a prescribed fire.

LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviation	Meaning
ΔNBR	Differenced Normalized Burn Ratio
3D-PFCN	3D Parallel fully Convolutional Network
ABi-LSTM	Attention enhanced Bidirectional LSTM Network
ADCIF	Agency for Protection against Forest Fires
AEMET	Agencia Estatal de Meteorología
AGB	Aboveground Biomass
ANN	Artificial Neural Network
AUC	Area Under the receiver operating characteristic Curve
AWAP	Australian Water Availability Project
BC	British Columbia
BN	Bayesian Network
BpS	Biophysical Settings
BRT	Boosted Regression Tree
BUI	Buildup Index
CAPE	Convective Available Potential Energy
CART	Classification and Regression Trees
CBD	Canopy Bulk Density
CBH	Canopy Base Height
CBI	Continuous Boyce index
CC	Canopy Cover
CFDB	Corsican Fire Database
CLDN	Canadian Lightning Detection Network

CO_2	Carbon Dioxide
CWFIS	Canadian Wild-land Fire Information System
DC	Drought Code
DEM	Digital Elevation Model
DGVMs	Dynamic Global Vegetation Models
DM	Dry Matter Content
DMC	Duff Moisture Code
DRL	Deep Reinforcement Learning
DTM	Digital Terrain Model
DWD	Deutsche Wetter Dienst
EC	European Commission
EFFIS	European Forest Fire Information System
EGIF	Estadística General de Incendios Forestales
EPA	Environmental Protection Agency
ERC	Energy Release Component
EROS	Earth Resources Observation and Science
EU	European Union
EWT	Equivalent Water Thickness
FAR	False Alarm Reduction
FBP	Fire Behaviour Prediction
FFDI	Forest fire danger index
FFMC	Fine Fuel Moisture Code
FMC	Fuel moisture content
FOP	Fire Occurrence Prediction
FPA	Fire Program Analysis

FRI	Fire Risk Index
FWI	Fire Weather Index
GAP	Gap Analysis Program
GIS	Geographical Information System
GISS	Goddard Institute for Space Studies
GOES	Geostationary Operational Environmental Satellites
GPS	Global Positioning System
HDF-EOS	Hierarchical Data Format Earth Observing System
HRV	Historical Range and Variation
HT	Canopy Height
IR	Infrared
ISI	Initial Spread Index
k-NN	k-Nearest Neighbours
LAADS	Level-1 and Atmosphere Archive & Distribution System
LANCE	Land Atmosphere Near-real time Capability for EOS
LDA	Linear Discriminant Analysis
LDN	Lightning Detection Network
LDS	Linear Dynamical Systems
LDSS	Low-Dimensional Summary Statistics
LiDAR	Light Detection and Ranging
LOPEX	Leaf Optical Properties Experiment
LP DAAC	Land Processes Distributed Active Archive Center
LR	Linear Regression
LSTM	Long Short Term Memory
LVNP	Lassen Volcanic National Park

MAGRAMA	Ministerio de Agricultura, Alimentación y Medio Ambiente
MARS	Multivariate Adaptive Regression Splines
MDPs	Markov Decision Processes
MFMCi	Model Free Monte Carlo with indices
ML	Machine Learning
MLP	Multilayer Perceptron
MLR	Multiple linear regression
MODIS	Moderate-resolution Imaging Spectroradiometer
MTBS	Monitoring Trends in Burn Severity
NAM	North American monsoon
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NDVI	Normalised Differential Vegetation Index
NEX-DCP30	NASA Earth Exchange downscaled climate models
NOAA	National Oceanic and Atmospheric Administration
NUTS	Nomenclature of Territorial Units for Statistics
NWP	Numerical Weather Prediction
OGC	Open Geospatial Consortium
OWA	Ordered Weighted Averaging
PCA	Principal Components Analysis
POMDP	Partially Observable Markov Decision Process
PSA	Predictive Services Area
QDA	Quadratic Discriminant Analysis

RAWS	Remote Automated Surface Weather Stations
R-CNN	Regions with Convolutional Neural Networks
RF	Random Forest
RM	Regularisation Multiplier
ROC	Receiver Operating Characteristic
SA	Spatial autocorrelation
SCRPPLE	Social-Climate Related Pyrogenic Processes and their Landscape Effects
SGB	Stochastic Gradient Boosting
SOM	Self-Organizing Map
SSD	Single Shot Detector
SVM	Support Vector Machines
SWA	Southwest area
UAV	Unmanned Aerial Vehicles
UNFCCC	United Nations Framework Convention on Climate Change
USDA	United States Department of Agriculture
UTM	Universal Transverse Mercator
VIIRS	Visible Infrared Imaging Radiometer Suite
VOC	Visual Object Classes
WAI	Wildland agriculture interface
WSN	Wireless Sensor Network
WUI	Wildland-Urban Interface
YOLO	You Only Look Once

EXECUTIVE SUMMARY

TREEADS is a European project co-funded by the H2020 research and innovation programme under the Grant Agreement No 101036926. In particular, TREEADS aims to develop new products and integrate them into a holistic Fire Management platform aimed at optimising and reusing the existing socio-technological resources. To this end, TREEADS consists of ten Work Packages (WPs) that define the administrative and technical activities. This deliverable is part of WP3, which aims to define Organisational, Structural, and Sociotechnical Factors for TREEADS Ecosystem Building and modular approach.

In the context of Task 3.1, Deliverable 3.1 (D3.1) will compile and detail the necessary studies about ecological and environmental models, thus providing a clear roadmap about the definition and implementation of the TREEADS models and services during the lifecycle of the project. For this purpose, a comprehensive literature review is conducted, taking into account multiple factors and criteria, while an initial description of the TREEADS models is given according to the activities of the various partners within the project.

Based on the aforementioned remarks, this report consists of 5 sections. The first section provides an introduction to the deliverable, presenting the objectives, the relation with the other deliverables and finally, its structure. Next, section 2 presents the methodology followed in this deliverable. Subsequently, according to the existing literature, section 3 focuses on the various wildfire-related models. In particular, the various models are organised based on three main categories: (a) Prevention and Preparedness Models, (b) Detection and Response Models and (c) Restoration and Adaptation Models. For each category, various criteria are investigated, such as environmental factors, weather data, socio-economic factors and fire data. Next, section 4 is devoted to the TREEADS wildfire models and services that will be implemented during the project. For each model, an initial description is provided according to the activities of the technical partners. Finally, section 5 concludes this report.

INTRODUCTION

PURPOSE OF THE DELIVERABLE

The goal of this deliverable is twofold: first, to provide a roadmap about the definition, the architectural design and the implementation of the TREEADS wildfire models and services that will be implemented during the project and second, to provide an initial description of them. Therefore, a comprehensive literature review is carried out, investigating in detail various wildfire-related models. In particular, three main categories are examined, namely (a) Prevention and Preparedness Models, (b) Detection and Response Models and (c) Restoration and Adaptation Models. For each category, various models are described based on multiple criteria and factors. Next, according to this analysis, the models and services offered by the TREEADS partners are identified and detailed, taking into account the requirements of WP2. Finally, the scope and type of the TREEADS models are identified, while also the role of the contributing partners is provided.

RELATION WITH OTHER WPS, TASKS AND DELIVERABLES

This deliverable is related to the following WPs, tasks, and deliverables based on the Grant Agreement.

- WP2/ Task 2.3- Prevention and Preparedness Understanding and Technical Requirement. Task 2.3 specific functional and not functional Requirements in the Prevention and Preparedness phase of wildfires were applied as input to the current deliverable.
- WP2/ Task 2.4- Detection and Response Understanding and Technical Requirement. Task 2.4 specific functional and not functional Requirements in the Detection and Response phase of wildfires were applied as input to the current deliverable.
- WP2/ Task 2.5- Restoration and Adaptation Understanding and Technical Requirement. Task 2.3 specific functional and not functional Requirements in the Restoration and Adaptation phase of wildfires were applied as input to the current deliverable.
- WP3/ Deliverable D3.2- Live doc TREEADS Organisational Structural and Sociotechnical factors V1. D3.1 will be integrated after the first version in D3.2 in a live document format.

STRUCTURE OF THE DELIVERABLE

This report is structured as follows.

- Section 1 – Introduction: Section 1 provides an introduction to this deliverable.
- Section 2 – Methodology: Section 2 provides the methodological framework used for the wildfire ecological and environmental modelling research and classification.
- Section 3 – Wildfire Ecological and Environmental Modelling: Section 3 provides comprehensive literature research on models and services outlining their applications.

- Section 4 –TREEADS Wildfire Propagation Models and Services: Section 4 describes the TREEADS partners models and their specifications.
- Section 5 – Conclusions: Section 5 concludes this report.

METHODOLOGICAL FRAMEWORK

The purpose of this deliverable is to provide a roadmap about the TREEADS models and services that will be implemented during the project. Consequently, to this end, the methodology illustrated in Figure 1 Methodology is followed. In particular, according to the WP2 requirements, three main categories with different scopes are defined: (a) Prevention and Preparedness, (b) Detection and Response and (c) Restoration and Adaptation. The first category aims to provide models and services that will mitigate malicious activities in a timely manner. Moreover, appropriate preparation activities lie in this category. The next category refers to detection and response countermeasures, while the last category focuses on restoration and remedial activities. Thus, based on the existing literature, various models are investigated, taking into account various criteria. In particular, the following criteria are considered for each category.

- **Prevention and Preparedness**: Weather data, environmental factors, socio-economic factors, historical fires, landscape management, fire occurrence observations, response management and methods.
- **Detection and Response**: Weather data, fire and smoke detection methods, environmental management, fuel consumption, fire spread rate and methods.
- **Restoration and Adaptation**: Weather data, environmental factors, fire data, restoration and adaptation techniques, socio-economic factors and methods.

Moreover, it is worth mentioning that for each of the above methods, particular subcategories are further defined, while novel Artificial Intelligence (AI) and statistical analysis methods are considered.

Next, based on the above analysis, an initial version of the TREEADS wildfire models and services are identified. First, a detailed description of the model is provided. Next, the scope and the type of the model are defined. Next, the input and the output of the model are given. Subsequently, potential standards and standardisation activities related to the model function are provided. Then, the WP2 requirements and the relevant use cases/pilots are identified. Finally, the role of each partner with respect to the definition and implementation of the model is provided.

Existing literature employs either or both of the terms "forest fire" and "wildfire." According to [1] [2] the term forest fire is “any wildfire or prescribed fire that is burning in forested areas, grass, or alpine/tundra vegetation”, while the term wildfire means “an unplanned or unwanted natural or human-caused fire, as contrasted with a prescribed fire”. Consequently, in this deliverable, these terms are used contextually, adhering to the definitions provided in the referenced paper.

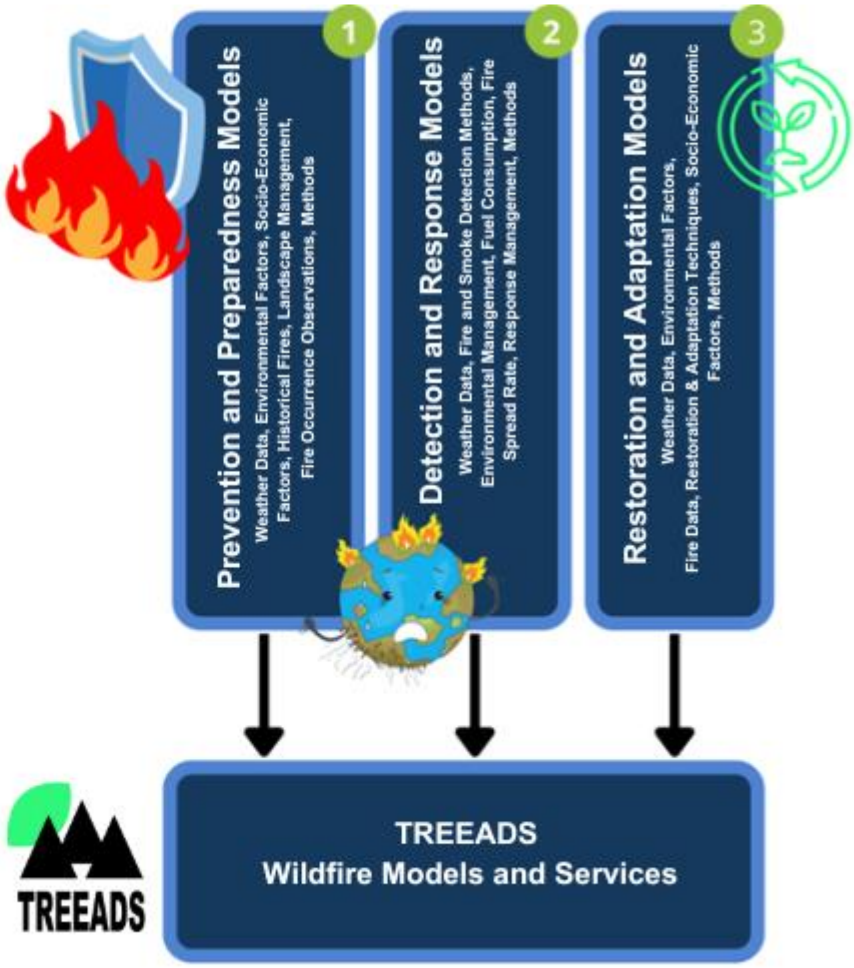

Figure 1 Methodology

WILDFIRE ECOLOGICAL AND ENVIRONMENTAL MODELLING

In the following sections, different models within each of the three primary categories i.e., Prevention and Preparedness, Detection and Response, and Restoration and Adaptation will be presented. Each category considers various criteria to address the specific challenges associated with wildfire management. Of particular significance in these models is the consideration of climate change, as it significantly impacts each of the categories.

Transfer modelling, whereby a model produced for one study region and (or) distribution of environmental conditions is applied to other cases, is a common approach in climate change science. Model transferability should be considered when applying ML methods to calculate projected quantities due to climate change or other environmental changes. With forest studies in the context of species distribution modelling have indicated that ML approaches may be suitable for transfer modelling under future climate scenarios.

There are various publications on wildfires and climate change that apply ML approaches. Amatulli et al. [3] found that multivariate adaptive regression splines (MARS) were better predictors of future monthly area burned for five European countries compared with multiple linear regression and RF. Parks et al. [4] projected fire severity for future time periods in the western US using BRT. Young et al. [5] similarly used BRT to project future fire intervals in Alaska and found up to a fourfold increase in (30-year) fire occurrence probability by 2100. Several authors used MaxEnt to project future fire probability globally [6], in the US Pacific Northwest (Davis et al. [7]).

The impacts of climate change on wildfires have received increased attention in recent years at both continental and local scales. It is widely recognised that weather plays a key role in extreme fire situations. It is therefore of great interest to analyse projected changes in fire danger under climate change scenarios and to assess the consequent impacts of wildfires. The authors in [3] estimated burned areas in the European Mediterranean (EU-Med) countries under past and future climate conditions. Historical (1985-2004) monthly burned areas in EU-Med countries were modelled by using the Canadian FWI. Monthly averages of the Canadian FWI sub-indices were applied as explanatory variables to estimate the monthly burned areas in each of the five most affected countries in Europe using three different modelling approaches (MLR, RF, MARS). MARS outperformed the other methods. Regression equations and significant coefficients of determination were obtained, although there were noticeable differences from country to country. Climatic conditions at the end of the 21st Century were simulated using results from the runs of the regional climate model HIRHAM in the European project PRUDENCE, considering two IPCC SRES scenarios. The MARS models were used for both scenarios resulting in projected burned areas in each country and in the EU-Med region. Results showed that significant increases, 66% and 140% of the total burned area, can be expected in the EU-Med region under the 2 scenarios, respectively.

Fire regime characteristics in North America are expected to alter over the next several decades as a result of anthropogenic climate change. Although some fire regime characteristics are relatively well-researched in the context of a changing climate, fire severity has not been as well-studied. The authors in [4] applied observed data from 1984 to 2012 for the western United States (US) to develop a statistical model of fire severity as a function of climate. This model was used for several (n = 20) climate change projections representing mid-century (2040–2069) conditions under the RCP 8.5 scenario. Model predictions show a widespread reduction in fire severity for large portions of the western US. Although, the proposed model implicitly encompasses climate-induced changes in vegetation type, fuel load, and fire frequency. The predictions are best translated as a potential reduction in fire severity, a potential that may not be realised due to human-induced disequilibrium between plant communities and climate. Consequently, to realise the reductions in fire severity predicted, land managers in the western US could facilitate the transition of plant communities towards a state of equilibrium with the emerging climate through means such as active restoration treatments and passive restoration strategies like managed natural fire. Resisting changes in vegetation composition and fuel load via activities such as aggressive fire suppression will enhance disequilibrium conditions and will likely result in higher fire severity in future decades because fuel loads will advance as the climate gets warmer and fire danger becomes more extreme. The results provide insights into the advantages and disadvantages of resisting or facilitating change in vegetation composition and fuel load in the context of a changing climate.

Boreal forests and arctic tundra cover 33% of the global land area and store an estimated 50% of total soil carbon. Because wildfire is a critical driver of terrestrial carbon cycling, enhancing fire activity in these ecosystems would likely have global implications. To predict potential spatiotemporal variability in fire-regime shifts, the authors in [98] modelled the spatially explicit 30-yr probability of fire occurrence as a function of climate and landscape features across Alaska. BRT models acquired the spatial distribution of fire across boreal forest and tundra ecoregions, highlighting summer temperature and annual moisture availability as the most influential of historical fire regimes. Modelled fire–climate relationships revealed distinct thresholds to fire occurrence, with a nonlinear increase in the probability of fire above an average July temperature of 13.4°C and below an annual moisture availability of approximately 150 mm. To predict potential fire-regime responses to 21st-century climate change, the BRTs were adapted with Coupled Model Intercomparison Project Phase 5 climate projections under the RCP 6.0 scenario. Based on these projected climatic changes, the results demonstrate an increased probability of wildfire in Alaskan boreal forest and tundra ecosystems, but of varying magnitude across space and throughout the 21st century. Regions with historically low flammability, including tundra and the forest-tundra boundary, are especially vulnerable to climatically induced changes in fire activity, with up to a fourfold increase in the 30-yr probability of fire occurrence by 2100. The results underscore the climatic potential for novel fire regimes to develop in these ecosystems, relative to the past 6000–35 000 yr.

Future disruptions to fire activity will threaten ecosystems and human well-being throughout the world, yet there are few fire projections at global scales and almost none from a broad range of global climate models (GCMs). Here [6], the authors integrate global fire datasets and environmental covariates to build spatial statistical models of fire probability at a 0.5° resolution and examine environmental controls on fire activity. Fire models are driven by climate norms from 16 GCMs (A2 emissions scenario) to assess the magnitude and direction of change over two time periods, 2010–2039 and 2070–2099. From the ensemble results, the authors identify areas of consensus for increases or decreases in fire activity, as well as areas where GCMs disagree. Although certain biomes are sensitive to constraints on biomass productivity and others to atmospheric conditions promoting combustion, substantial and rapid shifts are projected for future fire activity across vast portions of the globe. In the near term, the most consistent increases in fire activity occur in biomes with already somewhat warm climates; decreases are less pronounced and concentrated primarily in a few tropical and subtropical biomes. However, models do not agree on the direction of near-term changes across more than 50% of terrestrial lands, highlighting major uncertainties in the next few decades. By the end of the century, the magnitude and the agreement in direction of change are projected to increase substantially. Most far-term model agreement on increasing fire probabilities (~62%) occurs at mid- to high-latitudes, while agreement on decreasing probabilities (~20%) is mainly in the tropics. Although these global models demonstrate that long-term environmental norms are very successful at capturing chronic fire probability patterns, future work is necessary to assess how much more explanatory power would be added through interannual variation in climate variables. This study provides the first examination of global disruptions to fire activity using an empirically based statistical framework and a multi-model ensemble of GCM projections, an important step toward assessing fire-related vulnerabilities to humans and the ecosystems upon which they depend.

PREVENTION AND PREPAREDNESS MODELS

Preparedness can be described as a state of readiness to respond to a disaster, crisis, or any other type of emergency situation. In general, preparedness activities can be characterised as the human component of predisaster hazard management. Training and public education are the most utilised preparedness activities, and, when properly utilised, they have the potential to help people survive disasters. Although preparedness activities cannot prevent a disaster from occurring, they are very effective at ensuring that people know what to do once the disaster has happened.

In its classical meaning, prevention refers to a sustained action taken to reduce or eliminate risk to people and property from hazards and their effects. Prevention activities address either or both of the two components of risk, which are probability and consequence. By preventing either of these components, the risk becomes much less of a threat to the affected population. In the case of natural disasters, the ability of humans to limit the probability of a hazard is highly dependent on the hazard type, with some hazards impossible to prevent such as hurricanes or tornadoes, while avalanches, floods, and wildfires are hazards that the rate of occurrence can be limited. In general, however, prevention efforts for natural hazards tend to focus on improved consequence management. In terms of man-made disasters, however, there is a much greater range of opportunities to minimise both the probability and the consequences of potential incidents, and both are applied with equal intensity.

Based on the aforementioned remarks, this section focuses on prevention and preparedness models based on seven sub-categories (Figure 2), namely (a) fire weather prediction, (b) lightning prediction, (c) fire occurrence prediction, (d) fire management, (e) planning and policy, (f) wildfire preparedness and (e) social factors. For each subcategory, relevant works are detailed. Table 1 summarises these works in terms of weather data, environmental factors, socio-economic factors, historical fires, landscape management, fire occurrence observations, and methods.

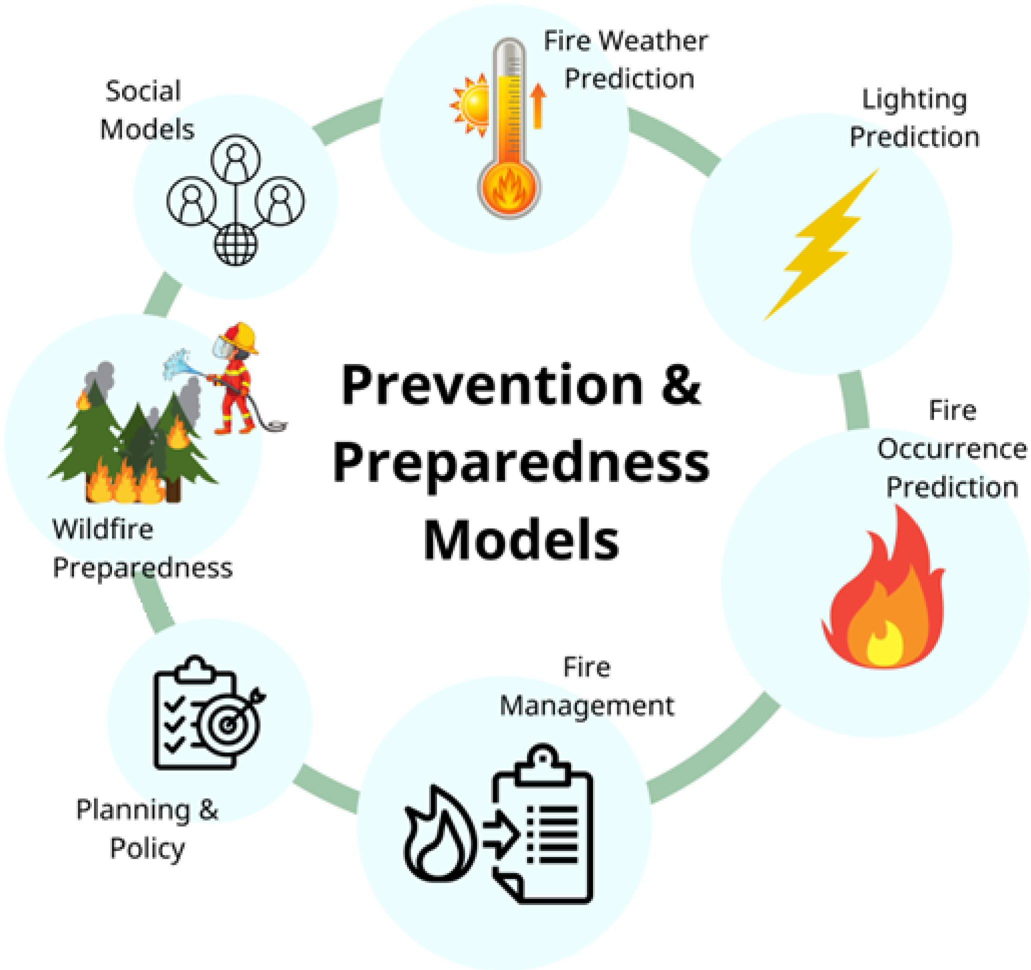

Figure 2 Sub-categories Prevention and Preparedness Models

FIRE WEATHER PREDICTION

The prediction of fire danger conditions allows forest management agencies to implement fire prevention, detection, and suppression action plans before fire damages occur. Although, in various countries, fire danger rating depends on observed weather data which only accounts for daily environmental monitoring of fire conditions [8]. Even when this estimation is improved with the combined use of satellite data, such as hot spots for early fire detection, and land cover and fuel conditions it normally only provides 4- to 6-hour warnings. By using forecast conditions from advanced numerical 20 weather models, an early warning could be extended up to 1-2 weeks allowing for greater coordination of resource-sharing and mobilisation within and across countries. [9] Due to the improved skills in weather forecasting, the use of numerical weather prediction (NWP) offers a real opportunity to enhance early warning capabilities [10], [11].

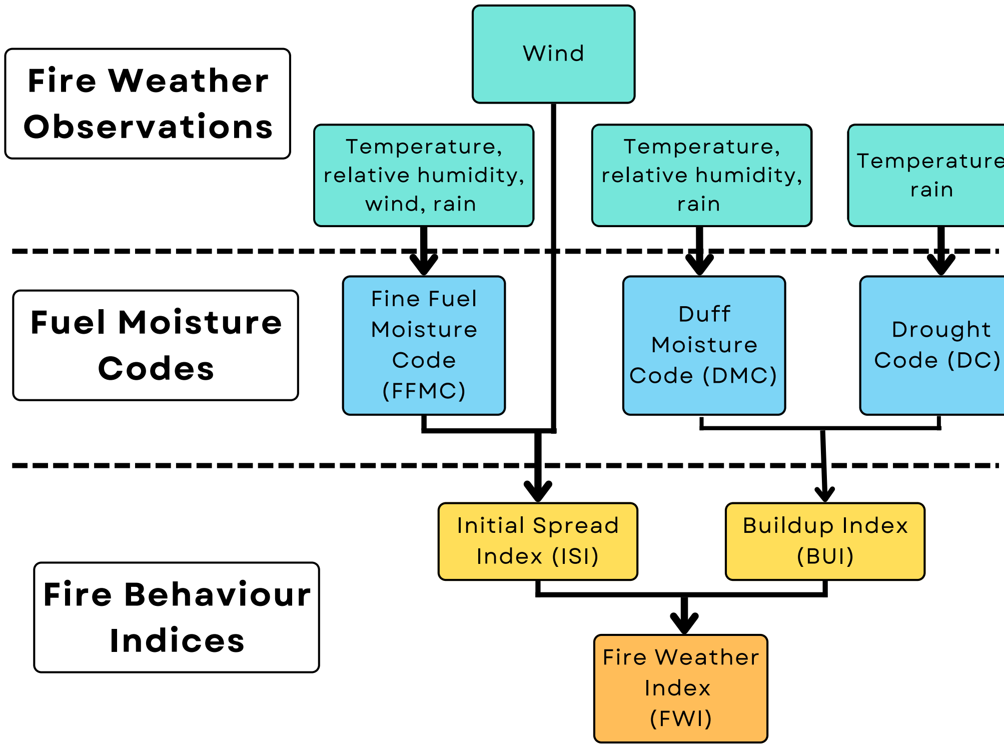

Figure 3 The FWI calculation Structure

The Fire Weather Index (FWI) [12] was developed by the Canadian method, involving weather parameters such as wind, relative humidity, surface temperature, and rain to describe the level of bush fire risk. The evaluation system of fire danger [13] is comprised of two subsystems: the Canadian FWI system and the Canadian system of fire forecasting [14]. This system utilises the Canadian method of the FWI [15]. This method was used in North America and Europe where very dense observation stations are and the results were very conclusive. Different indices characterise this index such as the state of fuel or the weather conditions on a specific point of the globe.

Fire weather is a determining critical factor if a fire will occur, the speed of the spread, and the location of the spread. Fire weather observations are usually acquired from surface weather station networks operated by meteorological services or fire management agencies. Weather observations are inserted from these point locations to a grid over the domain of interest, which incorporates diverse topographical conditions, the insertion task is a regression problem. Weather observations can subsequently be used in the calculation of meteorologically based fire danger indices such as the Canadian FWI System [12]. Future fire weather conditions and danger indices are commonly forecast using the output from NWP models [16], however, errors can accumulate in the calculation of fire danger indices that have a memory like the moisture indices of the FWI System. It is remarkable how surface fire danger measures can correlate with large-scale weather and climatic patterns.

The FWI System will obviously have different meanings in different forests or fuel types. The initial interest was mainly in logging slash of different types, but data linking spread rate with the FWI System in mixed forest and vegetation types has accumulated steadily. In fact, the FWI System is just part of the larger Canadian Forest Fire Danger Rating System (CFFDRS), which now includes the Canadian Forest Fire Behaviour Prediction (FBP) System, designed to provide quantitative estimates of fire behaviour in particular fuel types. An interim version of this latter provides equations for predicting the rate of spread in 14 vegetation and slash fuel types throughout Canada, as well as topographical adjustments and fire growth. It is in this line of work that further research and development will be concentrated in future.

The Fine Fuel Moisture Code (FFMC) represents the moisture content of litter and other cured fine fuels and indicates the relative ease of ignition and the flammability of fine fuel. The Drought Code (DC) is the average moisture content of deep, compact organic layers. This code depicts of seasonal drought effects on forest fuels and the amount of smouldering in deep duff layers and large logs. The Duff Moisture Code (DMC) is the average moisture content of loosely compacted organic layers of moderate depth and shows the fuel consumption in moderate duff layers and medium-size woody material. The Initial Spread Index (ISI) is a numeric rating of the expected rate of fire spread. It combines the effects of wind and the FFMC on a rate of spread without the influence of variable quantities of fuel. The Buildup Index (BUI) represents the total amount of fuel available for combustion. It combines the DMC and DC. The FWI express the fire intensity. It combines the Initial Spread Index and the Buildup Index. It is suitable as a general index of fire danger throughout the forested areas of Canada.

In West Africa, many types of research were conducted on the spatial and temporal distribution of fire activities. For better management, it is important to have preventive measures for bushfires with early warning systems through on-fire occurrences. FWI's products from the National Aeronautics and Space Administration (NASA) through the Goddard Institute for Space Studies (GISS) are used. The Figure 3 above depicts the structure of the fire weather index calculation.

The European Forest Fire Information System (EFFIS) was developed by the European Commission (EC) services and the relevant fires services in the countries such as forest fires and civil protection services in response to the requirements of European bodies such as the Monitoring and Information Centre of Civil Protection, the EC Services and the European Parliament. EFFIS is an extensive system encompassing the whole cycle of forest fire management, from forest fire prevention and preparedness to post-fire damage analysis. The system is providing information to over 30 countries in the European and Mediterranean regions and obtains comprehensive information on forest fire events from 22 European countries. It reinforces forest fire prevention and forest fire fighting in Europe via the provision of timely and reliable data on forest fires.

EFFIS essential applications are founded on the utilisation of remote sensing and geographic information systems. Two meteorological forecast models, handled by the French Météo-France and the Deutsche Wetter Dienst compute the fire danger forecast with the latter providing weather forecasts up to one week in advance. This information can be utilised to compute a common European fire danger index considering the Canadian FWI. Near-real time applications such as active fire detection and rapid damage assessment employ data provided by the MODIS sensor, onboard the NASA TERRA and AQUA satellites for the detection of hot spots (active fires) as well as mapping burnt areas. Daily two full mosaics of Europe are processed, providing data on burnt areas caused by large fires over 40 ha. The system architecture is established by web data services that grant access to data in real-time via web mapping and web feature service.

In [17], the aim of the study is to find the correlation between daily surface fire-weather index values to their respective synoptic circulation patterns and to characterise the environmental conditions within the key patterns. The author aims on creating an evaluation of the utility of automatic synoptic classification systems with respect to fire weather. This study's goal is to determine the synoptic weather patterns associated with elevated fire danger across the southwest United States and to examine the circulation patterns associated with three case studies of wildfire events. The seasonal continuum of synoptic types can be acknowledged to regulate whether seasonal changes in extreme fire-weather conditions are associated with changes in circulation patterns. The critical fire-weather patterns identified in this study have proven to be important to recent catastrophic wildfire events. Strong winds with the node 10, 20, and 30 weather types caused the Cerro Grande fire to burn more than 400 homes in Los Alamos, New Mexico. It is difficult to determine how often wildfire events interact with these critical circulation patterns. Long-term records of wildfire statistics typically do not provide daily progression summaries for the duration of wildfire events. Only recently have wildfires been documented in this way, limiting the present analysis to case studies. The identification of the climatology of these patterns may have utility in the planning capacity for prescribed burning activities. When used with weather forecasts prior to a prescribed burn, they can help elucidate possible changes in fire-weather conditions with respect to large-scale circulation features during the burn period.

In the analysis of [18], the authors examine various definitions and thresholds for determining the North American monsoon (NAM) onset and significant wildfire episodes within the SWA and its individual PSAs. The authors suggest that SOMs can help examine the intricate nonlinear relationships between the NAM and critical fire weather patterns leading to significant wildfire episodes. The SOMs implementation to identify synoptic patterns that correspond to the NAM onset and significant wildfire episodes including those atmospheric patterns that are prevalent before, during, and after these events. SOMs help infers the associated physical climate processes between the NAM and wildfire activity. Using atmospheric reanalysis data, gridded surface weather observations and historical wildfire datasets it can be demonstrated that the most frequently occurring synoptic patterns before and during the NAM modulate large wildfire occurrence. A method for determining the NAM onset by PSA as directly related to wildfire was also established corresponding to observed, and to some extent predictable, atmospheric patterns that promote increased moisture and lightning. The authors provided novel results documenting MTs directly associated with significant wildfire episodes and NAM onset in the SWA. The results of this work are intended to provide decision support information and improve understanding of atmospheric processes associated with NAM and their impact on wildfire activity. Improved understanding of this association may benefit operational fire meteorologists and managers by providing identifiable atmospheric patterns associated with elevated wildfire activity that is remarkably impactful on suppression resources and can encourage improvements in planning and logistical strategies.

LIGHTNING PREDICTION

Lightning is the second most common cause of wildfires thus, predicting the location and timing of future storms and strikes is of great importance to predicting fire occurrence. Electronic lightning detection systems have been deployed in various parts of the world for several decades and have accrued rich strike location–time datasets. The lightning prediction models that have employed this information to derive regression relationships with atmospheric conditions and stability indices can be forecast with NWP.

Lightning is one of the most common causes of wildland fires in Canada with 330 000 cloud-to-ground lightning strikes occurring. These strikes have ignited 45% of the reported 450 wildfires and caused 71% of the area burned 105 000 ha. Lightning-caused wildland fires in remote areas have large suppression costs and a greater chance of escaping initial attacks when compared with anthropogenic fires. The authors of [19] paired geographic and temporal covariates with meteorological reanalysis and radiosonde observations to generate a series of lightning prediction models valid from April to October. These models, based on cloud-to-ground lightning from the Canadian Lightning Detection Network, were created and tested for the province of Alberta in Canada. The forecasts derived from these models achieved the highest level of accuracy in the Rocky Mountain and Foothills Natural Regions, achieving hits rates of 85%. The Showalter index, latitude, elevation, longitude, Julian day and convective available potential energy are considered important predictors. RF classification is shown to be a usable modelling method for generating lightning forecasts.

Lightning paired with inconsequential rainfall is one of the most common natural ignition sources for wildfires globally. The authors in [20] presented a machine-learning and statistical classification analysis of 'dry' and 'wet' thunderstorm days relating to associated atmospheric conditions. This paper considered daily lightning flash count and precipitation information from ground-based sensors and gauges, as well as a comprehensive set of atmospheric variables based on the ERA-Interim reanalysis from 2004 to 2013. The locations studied represent a wide range of climatic zones. Quadratic surface representations and low-dimensional summary statistics were utilised to characterise the main features of the atmospheric fields. Four prediction skill scores were acknowledged and ten-fold cross-validation was utilised to evaluate the performance of each classifier. The results were compared with those gathered by adopting the approach used in an earlier study for the Pacific Northwest, United States. It was found that both approaches have prediction skills when tested against independent data, mean atmospheric field quantities proved to be the most influential variables in determining dry lightning activity and no single classifier or set of atmospheric variables proved to be consistently superior to their counterparts.

FIRE OCCURRENCE PREDICTION

Predictions of the number and location of fire ignitions in the prior days are critical for preparedness planning, as well as the procurement of resources, including the relocation of mobile resources and readiness for expected fire activity. The inception of fire occurrence prediction (FOP) models goes back almost 100 years. FOP models typically use regression methods to relate the response variable (fire reports or hot spots) to weather, lightning, and other covariance for a geographic unit or as a spatial probability.

The authors in [21] developed a system for the region of Galicia in Spain, one of the regions of Europe most afflicted by wildfires. During the 1990s, Galicia alone accounted for around 50% of all forest fires in Spain. Moreover, in the same period, the number of forest fires continued to grow despite an increase in the human and financial resources allocated to firefighting. The system developed in this study fulfils three main aims, to predict forest fire risks and therefore act as a crucial preventive tool by allowing fire-fighting units to focus on areas with the highest fire risk, to back up the forest fire monitoring and extinction phase and to assist in planning the recuperation of the burned areas. The aforementioned aims were achieved, from a technical point of view, using ANNs and expert systems. The forest fire prediction model based on a neural network uses meteorological data as the basis for assessing fire risk. The prediction obtained acceptable results using real data, bearing in mind that an intrinsic level of error that cannot be reduced occurs as a consequence of the significant number of fires that are intentionally caused in this area.

Fire danger rating systems are developed in various countries dealing with wildfire prevention and suppression planning so that civil protection agencies are capable to define areas with high probabilities of fire ignition and resort to essential actions. The authors in [22] showed a fire ignition risk scheme in the area of Lesvos Island, Greece, that can be an integral component of a quantitative Fire Danger Rating System. The presented methodology considers the geospatial fire risk despite the fire causes and the expected burned area, and it has the ability of forecasting based on meteorological data. The main output of the proposed scheme is the Fire Ignition Index, which is based on three other indices the FWI, the Fire Hazard Index, and the Fire Risk Index. The indices are not just a proportionate probability for fire occurrence, but a comparatively quantitative assessment of fire danger in a systematic way. Remote sensing data from the high-resolution QuickBird and the Landsat ETM satellite sensors were used to provide part of the input parameters to the scheme, while Remote Automatic Weather Stations and the SKIRON/Eta weather forecasting system depending on real-time and estimated meteorological information. Geographic Information Systems were employed for management and spatial analyses of the input parameters. The correlation between wildfire occurrence and the input parameters was investigated by neural networks whose training was based on historical data.

In [23], Vecín-Arias et al. assessed lightning-induced fire occurrence in the central plateau of the Iberian Peninsula established on the topography, vegetation, meteorology and lightning characteristics. In their study, the authors utilised two different methods: LR and RF. Information on the presence/absence of at least one lightning-induced forest fire in a 4 × 4 km grid cell in the period 2000–2010 was used as the dependent variable for model building, whereas information for the same period at a spatial resolution of 10 × 10 km was applied for model validation. Results demonstrate that five of the seven independent variables selected for each methodology were common to the two methods. The likelihood of a landscape being affected by lightning-induced fire depleted with increasing altitude and the percentage of agricultural crops, on the other hand, it was raised along with the percentages of coniferous and mixed woodlands as well as with the mean peak current of negative flashes. The percentages of coniferous woodlands and agricultural crops in a landscape were significant variables, displaying vegetation type as the primary factor to acknowledge when rating lightning-induced fire risk. The area under the receiver operator characteristics curves was estimated using the construction and validation datasets indicating similar and acceptable discrimination capacities for the two methodologies. The spatial analysis of misclassified predictions showed slightly better performance of the RF model, highlighting that this method has the potential for assessing lightning-induced fire occurrence. The understanding obtained can be valuable for spatially explicit assessment of lightning-induced fire risk, planning and coordinating regional efforts to determine the areas at greatest risk and designing long-term wildfire management strategies.

In [24], Van Beusekom et al. assessed the relationships between weather patterns and the probability of fire occurrence in the Caribbean. The cumulative effect of small frequent fires can shape large landscapes, and fire-prone ecosystems are abundant in the tropics. Furthermore, climate change can greatly expand fire-prone areas to moist and wet tropical forests and grasslands that have been traditionally less fire-prone and extend and create more temporal variability in fire seasons. In this study, the authors developed a ML RF classifier to analyse the correlation between climatic, socio-economic, and fire history data with fire occurrence and extent for the years 2003–2011 in Puerto Rico, with nearly 35,000 fires. Using classifiers based on climate measurements alone, the authors found that the climate space is a reliable associate, if not a predictor, of fire occurrence and extent in this environment. The authors showed a strong correlation between occurrence and a change from average weather conditions, and between the extent and severity of weather conditions. The probability of the RF classifiers indicating a positive example higher than a negative example is 0.8–0.89 in the classifiers for determining if a fire occurs, and 0.64–0.69 in the classifiers for determining if the fire is greater than 5 ha. Climate projections for the future extreme seasons indicate increased potential for fire occurrence with larger extents.

Increasing Australian bush-fire frequencies over the last decade have highlighted the major climatic change in the coming future. Understanding such climatic change for Australian bush-fire is limited and there is a crucial need for scientific research, which is capable enough to contribute to Australian society. The frequency of bush-fire carries information on spatial, temporal and climatic aspects of bush-fire events and provides contextual information to model various climate data for accurately predicting future bush-fire hot spots. In this study [25], the authors created an ensemble method based on a two-layered ML model to indicate the correlation between fire incidence and climatic data. In a 336-week data trial, Dutta et al. demonstrate that the model provides highly accurate bush-fire incidence hotspot estimation (91% global accuracy) from the weekly climatic surfaces. This study's analysis also indicates that Australian weekly bush-fire frequencies increased by 40% over the last 5 years, particularly during summer months, implicating a serious climatic shift.

In [7], Davis et al. utilised the data collected from large forest wildfires between 1971-2000 in the Pacific Northwest Region of the United States in order to create fire environment models. The models acknowledged the intrinsic elements of the fire environment such as vegetation which can be considered as fuel available for burning, as well as the climate, and the topography. The authors made sure to recognise a host of other factors that can help to explain the occurrence of wildfire, both environmental (e.g., historical lightning ignition density) and anthropogenic (e.g., distance to roads). The best model was produced using a regularisation multiplier (RM) setting of 2.0, with a continuous Boyce index (CBI) of 0.97 ± 0.02 and an area under the receiver operating characteristic curve (AUC) of 0.77 ± 0.01. The RM determines the penalty associated with including variables or their transformations in the model. Higher RM values impose a stronger penalty on model complexity and thus result in simpler (flatter) model predictions. CBI is the measure of the model accuracy for presence-only test data and AUC is the measure of the ability of a classifier to distinguish between classes. The modelling described in the paper combined new methods with old concepts to produce a time series of maps that showed how large wildfire environments might change within the forests of the Pacific Northwest Region under differing climate change scenarios.

In [26], the authors applied LR and RF approaches to identify the relative effects of climate and local factors on fire occurrence. The LR model was used to test the significance of each variable and the RF was applied to rank the relative importance of the significant variables. The utilisation of two different approaches allowed for the reach of a more comprehensive conclusion. The two methods provided similar results regarding driving factors and showed that climate factors are the basic drivers of fire occurrence in the forests of Fujian, China. Local factors were generally less significant. Of all the climate factors evaluated, sunshine hours, relative humidity (fire seasonal and daily), precipitation (fire season) and temperature (fire seasonal and daily) had affected fire occurrence the most. Of the local factors evaluated, elevation, distance to railway and per capita GDP were considered the most critical drivers of fire occurrence. The predictive ability of RF was higher than LR at all levels of factor analysis (climate, local and combined factors). Therefore, RF may be a more suitable approach for fire prediction. Maps showing the likelihood of forest fire occurrence detected fire-prone zones in Fujian, where more fire prevention resources such as fire towers, inspection stations, and patrol should be allocated.

In [27], Sayad et al. propose a strategy that makes use of big data and remote sensing to build a dataset, to be processed by Data Mining algorithms to predict the occurrence of wildfires. The aforementioned strategy is comprised of seven steps ranging from data collection to data extraction. The data were acquired from MODIS, a sensor embedded in both Terra and Aqua satellites. These data were made available by NASA's LP DAAC. The sensor was chosen because it covers the entire earth and provides a multitude of data products (e.g., NDVI: MOD13Q1, LST: MOD11A1, TA: MOD14A1) in regular and continuous time spans. Thus, the model can be utilised anywhere in the world. The originality of this paper lies within the fact of it seeks the development of a multi-disciplinary model for predictive analysis based on big remote sensing data and data mining. In this paper, an experiment has been set up to analyse the created dataset in order to predict the occurrence of wildfires in a specific region of Canada's forests between 2013 and 2014. The fire zones were acquired from the CWFIS. The constructed dataset is comprised of 804 instances (386 fire instances and 418 no fire instances). The experiment is considered a case study to illustrate what can be done on larger scales, for this reason, the dataset used in the simulation will not contain many instances. In this experiment, two of the most known data mining algorithms (ANN and SVM) were used, these algorithms were implemented in "Databricks", a big data platform. 70% of the data were used for training and the remaining 30% for testing. The results showed high FOP accuracy (ANNs: 98.32%, SVM: 97.48%). The model was validated using classification metrics, cross-validation, regularisation as well as a comparison with some existing wildfire models.

FIRE MANAGEMENT

The goal of contemporary fire management is to have the appropriate amount of fire on the landscape, which may be accomplished through the management of vegetation, including prescribed burning, the management of human activities (prevention), and fire suppression. Fire management is a form of risk management that seeks to maximise fire benefits and minimise costs and losses. Fire management decisions have a wide range of scales, including long-term strategic decisions about the acquisition and location of resources or the application of vegetation management in large regions, medium-term tactical decisions about the acquisition of additional resources, relocation, or release of resources during the fire season, and short-term real-time operational decisions about the deployment and utilisation of resources on individual incidents. Fire preparedness and response is a supply chain with a hierarchical dependence. Taylor describes 20 common decision types in fire management and maps the spatiotemporal dimensions of their decision spaces. Fire management models can be predictive, for example, the probability of initial attack success, or prescriptive as in maximising or minimising an objective function (e.g., optimal helicopter routing to minimise travel time in crew deployment). While advances have been made in the domain of wildfire management using ML techniques, there have been relatively few studies in this area compared with other wildfire problem domains. Thus, there appears to be great potential for ML to be applied to wildfire management problems, which may lead to novel and innovative approaches in the future.

In [28], Taylor utilised an interdisciplinary approach to investigate variability in fire weather, fire activity and fire management decision spaces in western Canada from three separate perspectives. The author used time-series analysis to identify periodic and quasi-periodic components of fire weather measures at second, hourly, daily, yearly, and multi-decadal resolution in 3 ecozones. Examples of correlation between scales of fire weather and fire activity were researched from the literature. Through interviews with and observation of Canadian wildland fire management agencies, 20 typical decision problems were identified of which 16 spatiotemporally cohesive decision spaces were mapped extending from incident to national levels and prompt to multi-decadal time spans. To connect these domains, space-time cascades of atmospheric kinetic energy are proposed to reflect in an inverse cascade of wildfire activity and shape the Spatio-temporal dimensions of decision spaces and the pace of fire management decisions. It is noteworthy that as the time scale decreases on critical days, fire activity can increase sharply in hours or minutes in response to rapid changes in weather, the time for decision making is decreased and weather and predictive models have restricted utility, quick intuitive judgements may supersede slower rational thought processes.

In [29], Loehman et al. identify three experimental approaches for landscape modelling that address the management challenges resulting from uncertain climate futures and complex ecological interactions: historical-comparative, future comparative, and threshold detection approaches. A historical-comparative approach compares contemporary or projected future conditions to the range and variation of historical conditions ("historical range and variation," or HRV). Historical, baseline conditions are generally defined as the period prior to European settlement, often corresponding to the availability of tree-ring or other long-term ecological records, although increasing recognition of the extent and importance of earlier human-caused landscape transformations warrants extending the HRV envelope to earlier periods in time. In a future comparative approach, multiple scenarios ("futures") are simulated over decades or centuries and results are used to evaluate ecosystem responses to perturbations and assess the impacts of management. The threshold detection approach establishes integral thresholds of climate or disturbance that generate rapid and persistent transformations of ecological systems such as loss of resilience. In many cases, ecological attributes show a minimal change until a critical environmental threshold is reached.

The authors in [30] tackled the challenge of quantitative risk analysis for wildland fire. Quantitative fire risk analysis relies on characterising and linking fire behaviour probabilities and effects. Fire behaviour probabilities are different from fire occurrence statistics (historic numbers or probabilities of discovered ignitions) because they depend on spatial and temporal factors controlling fire growth. That is, the probability of fire burning a specific area is dependent on ignitions occurring off-site and the fuels, topography, weather, and relative fire direction allowing each fire to reach that location. The development of a quantitative risk assessment procedure is based on spatially characterising fire probabilities, fire behaviour distributions, and value changes from those fires. In future studies simulation or characterisation of fire behaviour distributions and probabilities should be accomplished across large landscapes. Given the difficulty with these calculations, most risk assessments will likely be driven mainly by susceptible values rather than on the probability of fire behaviours or fire-related loss. Although this procedure may illustrate the locations of the valuable property relative to hazards and opportunities for land management, it does not factor in the likelihood of loss. Therefore, without an expected net value change it is impractical to calculate the cost-effectiveness of management activities for mitigating potential fire impacts.

PLANNING AND POLICY

A critical area of fire management is planning and policy, and various ML methods have been endorsed to address pertinent challenges. Bao et al. optimised watchtower locations for forest fire monitoring. Ruffault and Mouillot [31] assessed the impact of the fire policy introduced in the 1980s on fire activity in southern France and the relationships between fire and weather, and McGregor et al. [32] developed fast-running simulations (based on the FARSITE simulator) and interactive visualisations of forest futures over 100 years based on alternate high-level suppression policies. McGregor et al. [33] also showed how various ML and optimisation methods could be utilised to develop an interactive approximate simulation tool for fire managers. The authors of the aforementioned study utilised a modified version of the FARSITE fire-spread simulator, which was augmented to run thousands of simulation trajectories while including new models of lightning occurrences, the duration of the fire, and a forest vegetation simulator. McGregor et al. showed how to analyse a hierarchy of decision thresholds for deciding whether or not to suppress a fire, their hierarchy splits into fuel levels, then intensity estimations, and finally weather predictors to arrive at a generalisable policy.

In [34], Bao et al. suggested that integrating location models and visibility analysis can aid in efficiently placing watchtowers for forest fire monitoring on the terrain. The authors detailed the procedure of data preparation using viewshed analysis in a GIS and optimisation models based on the location set covering the problem and the maximum covering location problem. The authors demonstrated how multiple types of watchtowers can be incorporated into the optimisation models and how a bi-objective optimisation model can be used to help explore the trade-off between the coverage and the cost of locating forest fire monitoring facilities. The models developed in this paper can be applied in a broader context where other devices are used. The key to applying the models in a different situation is to determine the coverage of the device. The viewshed analysis aid in determining whether a location can be covered by validating whether that location is visible from a facility. This correlation of being visible can be extended to other devices as long as it is possible to determine whether a location can be sensed from the facility. It also can be noticed that while DEM is used to compute the viewshed in this paper, fires sometimes can be detected by their rising smoke plumes that are higher than the elevations on the DEM cells. While this does not change how the optimisation models can be developed, it indeed presents a significant challenge to the data preparation process. For vulnerable locations where there is a need for more secured monitoring, it is required to ensure that they are covered by more than one watchtower so that equipment failure at individual towers will not affect the monitoring process. In the bi-objective model, the authors also explore the impact of security gained on the overall cost by duplicating coverage, which will help decision-makers decide the level of security for special cases.

There is the belief among land managers and others that the protected status of many forestlands in the western United States coincides with higher fire severity levels due to historical restrictions on logging that contribute to greater amounts of biomass and fuel loading in less managed areas, especially after decades of fire suppression. This view has led to recent proposals at the administrative and the legislative level, to reduce forest protections and increase some forms of logging based on the belief that restrictions on active management have increased fire severity. The authors in [35] researched the correlation between protected status and fire severity using the RF algorithm applied to 1500 fires affecting 9.5 million hectares between 1984 and 2014 in pine and mixed-conifer forests of the western United States, considering key topographic and climate variables. It was deduced that forests with higher levels of protection had lower severity values even though they are generally identified as having the highest overall levels of biomass and fuel loading. The results suggest a need to reconsider current overly simplistic assumptions about the relationship between forest protection and fire severity in fire management and policy.

The interactions between anthropogenic and biophysical factors that control fire regimes are becoming a major concern in the context of climate, economic and social changes. On a short time, scale, fire activity is mainly driven by variations in weather conditions. But while the assessment of this fire-weather relationship is a critical part of fire hazard estimations, reconstructions or projections, a lot of gaps in the impact of human practices on this relationship exist. The authors in [31] researched the recent fire history in southern France where a new fire policy was introduced during the 1980s with new fire suppression and prevention practices. This study aimed to assess the impact the changes had on fire activity and on the correlation between fire and weather. A statistical framework based on spatially explicit daily fire occurrence data was utilised and the corresponding weather variables and the associated fuel moisture were derived from a process-based model. The results demonstrated that the introduction of the new fire policy resulted in a sharp decrease in fire activity but also impacted the daily fire-weather relationship in two main ways. Firstly, it was shown that fewer wildfires ignited in similar weather conditions. Lastly, the probability of a fire spreading over significant surfaces shifted from a fuel-dryness driven system to a system driven by the concomitance of fuel dryness and strong winds. These observations suggest that mid-term social factors can affect the short-term correlation between weather conditions and fire activity. Therefore, the interactions between human and climate factors should be considered when reconstructing or projecting fire activity and including the impact of fire policies on the fire-weather relationships in fire models would be an important step toward more realistic fire regimes simulations.

Managers of US National Forests are responsible for deciding which policy to apply for dealing with lightning-caused wildfires. The conflicts between the stakeholders (e.g., timber companies, homeowners, and wildlife biologists) have often caused political debates. By providing a high-fidelity simulation environment in which stakeholders can explore the space of alternative policies and understand the trade-offs it will mitigate the multistakeholder issue. An environment like the aforementioned requires support for fast optimisation of MDP policies so that users can adjust reward functions and analyse the resulting optimal policies. McGregor et al. [32] assess the suitability of SMAC, a black-box empirical function optimisation algorithm, for rapid optimisation of MDP policies. This study presents five reward function components and four stakeholder constituencies. It then introduces a parameterised class of policies that can be easily understood by the stakeholders. SMAC is deployed to detect the optimal policy in this class for the reward functions of each of the stakeholder constituencies. From the validation process, it can be confirmed that SMAC is able to quickly detect good policies that make sense from the domain perspective. Because the full-fidelity forest fire simulator is far too expensive to support interactive optimisation, SMAC is applied to a surrogate model constructed from a modest number of runs of the full-fidelity simulator. To check the quality of the SMAC-optimised policies, the policies are evaluated on the full-fidelity simulator. The results confirm that the estimates of the surrogate values are valid. This is the first successful optimisation of wildfire management policies using a full-fidelity simulation. This methodology is also applicable to other natural resource management problems where high fidelity simulation is extremely expensive.

In [33], McGregor et al. aim to support interactive MDP visualisation, therefore they utilise visual properties of the MDP visualisation MDPVIS to evaluate the performance of MFMCi.

The authors utilised the unitless measurement of "visual fidelity error," which is a measure of how similar MDPVIS looks under MFMCi when compared to the visualisation generated from the ground truth simulator. The authors demonstrate MFMCi on a computationally expensive wildfire, timber, vegetation, and weather simulator that takes hours to generate single trajectories. The aim of the wildfire management simulator is to inform wildfire suppression policies that determine whether the US government will suppress a wildfire. The fire simulator spreads fire spatially from an ignition point according to the surrounding pixel layers and the hourly weather sampled from 26 historical weather years. Weather variables include hourly wind speed, wind direction, cloud cover, minimum temperature, maximum temperature, temperature, humidity, and precipitation. In this study, MFMCi was used to synthesise trajectories by modelling the weather time series and ignition locations as exogenous variables. The weather is exogenous because, to a first approximation, neither the actions nor the landscape influence the weather. Ignition location is exogenous to the landscape because tree cover does not affect the ignition's spatial probability distribution. Additionally, timber harvest and vegetation growth are deterministic functions of the landscape, which means every state transition contains its results.

WILDFIRE PREVENTION

In [36], Penman et al. introduced spatial data, developed a process model and provided expert opinion in order to undertake a risk assessment of various fire management strategies. BNs provide the ideal framework for such a task and have been increasingly used in the field of risk assessment. The approach that was adopted would be broadly applicable to researchers in other natural disasters such as floods, droughts and earthquakes, where data is sparse but improving management practices may save lives and property. In this study analysis, it was shown that all strategies can result in a reduction in the risk of house loss from fires. However, meaningful recommendations to management require further consideration on the extent to which anyone action will be implemented which is going to be limited by social, environmental and economic factors. This study was based specifically on the point of loss and has not attempted to trade-off landscape management approaches such as fuel treatment and initial attack of ignitions.

In the occurrence of active fire incidents often the decisions are made under rapidly evolving conditions, with limited time to assess management strategies or to create backup plans if the initial efforts are found unsuccessful. Usually, extreme fire weather conditions, topography and fuels are prevalent factors influencing potential fire spread and burn severity. O'Connor et al. in [37], utilised the aforementioned to quantify the influence of topography, fuel characteristics, road networks and fire suppression effort on the perimeter locations of 238 large fires, and develop a predictive model of potential fire control locations ranging from fuel types to topographic features and natural and anthropogenic barriers to fire spread, on a 34 000 km2 landscape in southern Idaho and northern Nevada. The boosted logistic regression model classified the final fire perimeter locations with accuracy on an independent dataset with 69% accuracy without taking into account weather conditions on different fires. The resulting fire control probability surface can potentially for reducing unnecessary exposure for fire responders, coordinate pre-fire planning for operational fire response, and as a network of locations to assimilate into spatial fire planning to align fire operations with land management objectives.

Maintaining control of an aircraft using data from images is a high-dimensional control problem. One possible solution for this type of problem is DRL. Utilising raw images, the algorithm learns a policy to maximise the accumulation of rewards over time, leading to precise control in high dimensional state spaces. Preceding techniques for autonomous wildfire surveillance isolate the control system from the wildfire observations. However, wildfires can grow in ways difficult to predict, making planning trajectories difficult. In addition, feature extraction limits what information the controller can use to plan trajectories. Furthermore, hand-tuned controllers using image features may not generalise well among all possible images.

SOCIOECONOMIC MODELS

In recent years the utilisation of ML in fire management has developed to include more nuanced aspects of fire management, even encompassing the investigation of criminal motives related to arson. Delgado et al. [38] employed BNs to characterise wildfire arsonists in Spain, by understanding five motivational archetypes slight negligence, gross negligence, impulsiveness, profit, and revenge.

In [38] Delgado et al. constructed five archetypes for provoked forest fires by using an ad hoc BN model learned from a dataset. The archetypes were constructed from arsonist motivation, which is the most central author variable in the model and plays a critical role in psychological criminology, in accordance with the modes of procedure in criminal activities of Shye's model of the action system. In addition, the authors obtain a ratification of the five archetypes but with some specificities obtained thanks to the great potentiality of the used methodology. Although, the constructed BN models show the correlation between the different variables such as features of the wildfire and characteristics of the arsonist, including motivation, as well as the accurate understanding of these dependencies that allows obtaining predictions about some variables from others, without having to give up to take into consideration the complex relations that exist among them. As a matter of fact, the BN model captures these complexities and uses them in an efficient way.

In [39], Scheller et al. developed a new fire model the SCRPPLE that emphasises the social dimensions of fire, and captures, human ignitions, accidental or via prescribed fire, the spatial and temporal patterns of prescribed fires, fuel-treatment effects, the spatial patterns of fire suppression. In addition, SCRPPLE captures the effects of topography, fuels, and climate. The authors emphasised parameterisation using landscape-scale datasets that have recently become more widely available. The approach grants targeted emphasis on diverse processes. If suppression is not practiced on the landscape, it can be readily disabled. The fire model described could be operated without any information except the relationship between ignitions, spread, and FWI. Every model approach has inherent limitations and SCRPPLE is no exception; it requires substantial spatial and temporal data for sufficient parameterisation. Nonetheless, these data requirements are already being fulfilled, taking into account the large amount of remotely sensed imagery that has been collected over active fires.

In [40], Faramarzi et al. carried out applied research using the multi-criteria evaluation method, when the human, climatic, and environmental factors were considered to determine the areas with potential fire hazards in the Golestan National Park. The results highlighted the importance of human factors in the occurrence of fires in the study area, among which the transit road that passes through the park has the most significant impact on wildfires in the region greatly increases the importance of clearing the road from the park. Low risk and a few TRADEOFFS scenarios show, on average, the best performance among ordered weighted averaging OWA scenarios, which indicates the importance of the interaction of all variables in the incidence of fires. According to the fire risk mapping and assessment review, the results demonstrated that the accuracy of each method, despite the practical and usable maps, could be used in fire crisis management. To determine the fire risk maps using human, climatic, and environmental factors, each map can be used in special cases. For example, prevention and management programs using warning tools could be considered in areas where human factors are more prominent than the other ones. Moreover, making natural cut fire and cultivating fire-resistant species as well as preparing maps of wind patterns and high-temperature days could be useful strategies in forest fire management programs. A reasonable management approach to tackle this issue in the park could be suggested to design water tanks or build helicopter pads in high fire risk areas to fight the fire as quickly as possible.

In [41], the authors aimed in providing insight into the application of ML models for the assessment of human-caused wildfire occurrence. The utilisation of ML within the context of fire risk prediction, and in the evaluation of human-induced wildfires in Spain. ML approaches such as RF, BRT and SVM were implemented in comparison with traditional methods like LR. The results suggest that the application of any of these ML algorithms leads to an improvement in the accuracy in terms of the AUC of the model in comparison with the LR outputs. According to the AUC values, RF and BRT indicate to be the better methods, reaching AUC values of 0.746 and 0.730 respectively. On the other hand, despite the fact that the SVM yields an AUC value higher than that of LR, the authors consider it inadequate for classifying wildfire occurrences because its calibration is extremely time-consuming.

To conclude, this section has discussed prevention and preparedness models, effectively considering fire weather prediction, lightning prediction, fire occurrence prediction, fire management, but also planning and policy, wildfire preparedness and the various social factors associated with the process of preventing and preparing for wildfire events. Furthermore, the survey was conducted through a broad spectrum of research focusing on weather data, environmental and socio-economic factors, but also fire data, and how the aforementioned metrics affect landscape management, are interconnected with fire occurrence observations, and eventually result in effective response management methods. It can be deduced that currently, virtually all wildfire prevention efforts and mitigation measures for relevant natural hazards tend to focus on improving the management of the negative consequences and not the source of the issue. Especially in the case of man-made disasters, the need to directly tackle the source of the problem is highlighted, as human behaviour is arguable one of the most volatile yet least predictable factors associated with such events. Therefore, models that consider a broad spectrum in their training data have higher chances in aiding in the prevention and preparedness scope.

Table 1 Summary of Prevention and Preparedness Models

Reference	Weather Data	Environmental factors	Socio-Economic Factors	Historical-Fires	Landscape Management	Fire Occurrence Observations	Method
San-Miguel-Ayanz et al. [16]	French Météo-France and the Deutsche Wetter Dienst (DWD)	Moderate-resolution Imaging Spectroradiometer (MODIS) The Nomenclature of Territorial Units for Statistics (NUTS)	The NUTS European Office for Statistics (EuroStat)	The European Fire Database- 25 years for Mediterranean countries	MODIS	The MODIS sensor and the Open Geospatial Consortium (OGC) Sensor Observation Service	EFFIS
Crimmins [17]	Daily weather observations from 15 remote automated surface weather stations (RAWS) for April, May, and June for the period of 1988–2003	The National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR)	Not applicable	United States (Arizona and New Mexico) during the period of 1988–2003.	RAWS sites (black dots) and NCEP–NCAR Reanalysis grid cells used in SOM classification	Not applicable	Self-Organising Map (SOM) algorithm
Nauslar et al. [18]	National Weather Service Weather Forecast Office Tucson	NCEP	Not applicable	Southwest area (SWA) Predictive Services Area (PSA) April through	SWA (Arizona, New Mexico, west Texas, and Oklahoma Panhandle)	Fire Program Analysis (FPA)	SOM

				September from 1995–2013			
Blouin et al. [19]	NCEP-DOE The Canadian Lightning Detection Network (CLDN)	NCEP-DOE	Not applicable	Thirteen years of lightning and weather data were obtained for the years 1999 to 2011.	Alberta province, spanning an area of 661 848 km2, with six major Natural Regions	Not applicable	Random Forest (RF), Regression Tree,
Bates et al. [20]	Ground-based CIGRE 500 by the Australian Bureau of Meteorology	Convective Available Potential Energy (CAPE)	Not applicable	The records cover the period from January 2004 to at least December 2010 (Townsville) and at most February 2013 (Melbourne).	Histograms for sites located in western Australia (Perth and Port Hedland) and those in central and eastern Australia 458 (Darwin, Townsville, Coffs Harbour and Melbourne)	Not applicable	Low-Dimensional Summary Statistics (LDSS) Classification and Regression trees (CART), RF, linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and logistic regression (LR)
Alonso - Betanzos et al. [21]	Online acquisition of meteorological data: an independent module designed to obtain data, via the Internet, from the automatic	Databases that store information on previous fire control actions, the environment, records of meteorological variables,	socio-economic and terrain factors (i.e. existence of a road, type of vegetation, etc)	Historical information on fires that have occurred between 1988 and 2001	Geographical Information System (GIS)	The Universal Transverse Mercator (UTM) coordinates of the square in which each fire occurred	A neural network whose output is classified into four symbolic risk categories

	meteorological stations in Galicia	characteristics of the terrain, resources, etc.					The CommonKADS methodology
Vasilakos et al. [22]	Remote Automatic Weather Stations and the SKIRON/Eta weather forecasting system provided real-time and forecasted meteorological data	Expected fuel moisture was calculated based on the forecast relative humidity provided from the SKIRON/Eta model.	Consideration of the Fire Risk Index (FRI): fire risk at a particular area due to human presence.	Historical information on fires that occurred between 1970 and 2001 on the island of Lesvos.	QuickBird satellite data on Lesvos Island. Mediterranean-type climate, with warm and dry summers, mild and moderately rainy winters.	Not applicable	A neural network: multilayer perceptron (MLP) was trained through the method of error back-propagation.
Vecín-Arias et al. [23]	the Spanish Meteorological Agency (Agencia Estatal de Meteorología, AEMET)	The forest fire data was provided by the Spanish Ministry of Agriculture, Food and Environment (Ministerio de Agricultura, Alimentación y Medio Ambiente, MAGRAMA)	Humancaused wildland fires in the region, but naturally induced forest fires	1464 fires in the period 2000–2010.	The digital Spanish Forestry Map, digital terrain model (DTM) with a resolution size of 200 × 200 m, provided by the National Geographic Institute	The lightning detection network (LDN)	LR, RF
Van Beusekom et al. [24]	Daily maximum and minimum temperature and precipitation are recorded at National Weather Service Cooperative Observer stations	The National Digital Forecast Database	Use of unemployment as a predictor indicating socio-economic conditions	Fire history data with fire occurrence and extent for the years 2003–2011 in Puerto Rico,	Puerto Rico is the smallest of the Greater Antilles Islands, located in the northeastern Caribbean Sea. The main island is approximately	Not applicable	Artificial neural network (ANN), Binary logistic regression, RF, decisions Trees

	and interpolated across the island as daily climate surfaces from 2002 to 2011			nearly 35,000 fires.	8900 km2 with a thin strip of coastal plains, 8–16 km wide, surrounding steep igneous upland		
Dutta et al. [25]	Not applicable	NASA MODIS Active fire data product (based on satellite images from EOSDIS), Burned Area data product and Australian Water Availability Project (AWAP) data	Not applicable	Extensive research in Australian bush-fire history during 2007-2013	FIRMS data and imagery from the Land Atmosphere Near-real time Capability for EOS (LANCE) system operated by the NASA/GSFC/Earth Science Data and Information System (ESDIS)	NASA Active Fire and Burned Area data	An ensemble method based on a two-layered ML model to establish relationship between fire incidence and climatic data.
Davis et al. [7]	NASA Earth Exchange downscaled climate models (NEX-DCP30)	The fire environment of the 1971–2000 climate normal period.	Not applicable	Fire season climate based on the 1971–2000 climate normal data	216,900 km2 of forest land in Washing- ton and Oregon.	United States Department of Agriculture (USDA) Active Fire Mapping Program	MaxEnt version 3.3, he Parameter-elevation Regressions on Independent Slopes Model
Guo et al. [26]	Daily climate data was provided by the China Meteorological Data and Sharing Network	The Geographical Sciences and Resources Research Institute, Chinese Academy of Sciences. The	The Data Sharing Infrastructure of Earth System Science	MODIS for the Fujian province during the period 2000–2010	Fujian, a province of south-eastern China. Fujian has a total land area of 124 000 km	Not applicable	LR and RF

		NCEP/NCAR Modis Normalised Differential Vegetation Index (NDVI) and Digital Elevation Model (DEM) data					
Taylor [28]	Remote automatic fire weather stations operated by the British Columbia (BC) Wildfire Service and Saskatchewan Environment	BC Wildfire Service and Saskatchewan Environment	Not applicable	Not applicable	The 12 Canadian provincial and territorial wildfire management agencies, Parks Canada, and the Canadian Interagency Forest Fire Centre	Daily routing of detection aircraft	Time series analysis, hierarchical model
Loehman et al. [29]	Not applicable	FireBGCv2 landscape-scale, ecosystem-fire process model	The National Science Foundation Coupled Natural and Humans Systems Program	An historical comparative approach	FireBGCv2 landscape-scale, ecosystem-fire process model	Not applicable	Principal components analysis (PCA) of multivariate model, Simulation modelling is a dynamic field, challenged by ecological complexities and emerging, non-analogue system

							drivers and responses.
Finney [30]	Local weather records	Not applicable	Not applicable	Not applicable	Simulate random ignitions and artificial landscapes	Not applicable	Development of a quantitative risk assessment procedure is dependent on spatially characterizing fire probabilities, fire behaviour distributions, and value changes from those fires.
Bao et al. [34]	Not applicable	Greenpeace Research Laboratories and climate change research of United States Environmental Protection Agency (EPA)	Guangzhou Administration of Forestry and Municipality Garden, Construction project of park social security and key forest zone video monitoring system in Guangzhou City	Chinese forestry development, a total of 3966 forest fire incidences were identified in 2012	Longdong Forest Park that is part of the southern end of the Dayu Mountains, in the northeast of the city of Guangzhou, China. Forest covers 96 percent of the park	Coverage rate of forest fire monitoring has increased from 45.3 to 63.1 percent in China, Watchtower location models	Three application models specifically for locating watchtowers in a context of forest fire monitoring.

Bradley et al. [35]	The PRISM climate group	Level III ecoregions, U.S. EPA	Not applicable	1500 fires affecting 9.5 million hectares between 1984 and 2014 in pine (Pinus ponderosa, Pinus jeffreyi) and mixed-conifer forests of western United States	Geographic extent of forest types from the Biophysical Settings data set (BpS), ArcMap 10.3	Not applicable	RF, Spatial autocorrelation (SA), Gap Analysis Program (GAP)
Ruffault and Mouillot [31]	Daily weather variables were derived from the 8 × 8 km grid SAFRAN climatic database (CNRM France)	PROMETHEE fire database	Contrasted national and regional fire policies have been developed and introduced worldwide, Dynamic Global Vegetation Models (DGVMs)	Historical fire activity over the 1973–2006 period based on national information	PROMETHEE fire database	Not applicable	DGVMs, boosted regression trees (BRTs)
McGregor et al. [32]	Hourly weather sampled from 26 historical weather year	Not applicable	Not applicable	The surrounding pixel layers and the hourly	Generate visualisations for a landscape's development over	Not applicable	Model Free Monte Carlo with indices (MFMCi), Markov Decision

				weather sampled from 26 historical weather years.	100 year time spans		Processes (MDPs)
McGregor et al. [33]	Weather is simulated by resampling from the historical weather time series observed at a nearby weather station	A high-fidelity simulation environment in which stakeholders can explore the policy space	Not applicable	Weather is simulated by resampling from the historical weather time series observed at a nearby weather station	The landscape totals approximately one million pixels, each of which has 13 state variables that influence the spread of wildfire on the landscape. (OpenStreetMap)	Not applicable	MFMCi surrogate model, SMAC—a black-box empirical function optimisation algorithm
Penman et al. [36]	Richmond Bureau of Meteorology weather station (station number 67033)	The McArthur Forest fire danger index (FFDI), GIS data or Google Earth	If a resident prepares for wildfire and the community education level	daily FFDI from Richmond Bureau of Meteorology weather station (station number 67033) for the period from 1970 through to 2010.	The Sydney Basin Bioregion are three large urban centres (Sydney, Newcastle and Wollongong)	Not Applicable	Bayesian Networks (BNs)
O'Connor et al. [37]	the Trail Gulch Remote Automatic Weather Station	Not applicable	Not applicable	A spatial database of historical fire perimeter locations	The National Wildfire Coordinating Group, and an ,34 000 km2 landscape located in the northern Rocky Mountains	Not applicable	BRT and the MaxEnt package

					bordering Idaho, Nevada and Utah		
Delgado et al. [38]	Not applicable	Not applicable	A database consisting of policing clarified arson-caused wildfires under the leadership of the Prosecution Office of Environment and Urbanism of the Spanish state	Statistical information on the phenomenon of forest fires has been collected in Spain since 1968, by the General Directorate of Natural Environment and Forestry Policy of the Ministry of Agriculture and Fishery, Food and Environment of Spain.	Not applicable	Not applicable	BNs
Scheller et al. [39]	Daily fire weather data	LANDIS-II landscape simulation	Human ignitions, accidental or via prescribed fire	Utilised historical patterns for comparison	Lake Tahoe Basin is a dry conifer forest on the east side of the Sierra Nevada with a high average snowpack (50–150 cm) and dry summers.	Not applicable	Social-Climate Related Pyrogenic Processes and their Landscape Effects: SCRPPLE
Faramarzi et al. [40]	Maps of temperature, rainfall, pressure, and moisture were	Distance map of springs obtained with Global Positioning	Main road, side road, village, camping,	The forest fire locations were identified according to field	Distance map of springs obtained with GPS, NDVI map was obtained	Not applicable	Ordered weighted averaging (OWA) scenarios, IDRISI

	prepared from meteorological data, WRPLOT	System (GPS), NDVI map was obtained from 2017 Landsat 8 satellite images	hunters, shepherds	surveys, MODIS satellite images, and the historical fires recorded by the park authority during 1981–2018.	from 2017 Landsat 8 satellite images		Taiga and ArcGIS (Ver. 10.4, 2019) software.
Rodrigues et al. [41]	Not applicable	Spanish EGIF (General Statistics of Wildfires)	Forestry area in public utilities, Wildland-Urban Interface (WUI), Changes in demographic potential 1991-2006, WAI, Power lines, Density of agricultural machinery, Railways, Protected.	Spanish EGIF (General Statistics of Wildfires) database from 1988 to 2007.	Wildland-Urban interface	Spanish EGIF (General Statistics of Wildfires)	RF, BRTs, and Support Vector Machines (SVM), LR.
Taylor and Alexander [8]	Interpolation of data obtained between weather stations to achieve spatial variability in fuel, weather and terrain data.	Consideration of fuel typology, weather, topography	Consideration of the opinions of individuals in assessing risk and allocating resources.	Analysis of historical records on fire occurrence and weather data.	Not applicable	Not applicable	CFS-developed fire danger rating methods, integrating variables into numberical values

Roads et al. [10]	Fire weather index (FWI), NFDRS indices.	National Center for Environmental Predictions (NCEP)	Not applicable	Not applicable	Consideration of vegetation typologies depending on landscape characteristics and local fuel models.	Observed fire spread statistics and forecasts.	Global spectral model (GSM), Regional spectral model (RSM), Fire danger indices
Mölders [11]	Fire weather index (FWI), NFDRS indices, Weather Research and Forecasting (WRF) data.	Consideration of NCEP global final analyses (FNL) as the initial and boundary conditions	Not applicable	Consideration of wildfire history in Alaska.	Consideration of landscape characteristics unique to the Alaskan landscape.	Not applicable	WRF prediction of spatial distribution of precipitation evolution, localized prediction of fire indices.
Wagner [42]	Fuel moisture codes following daily changes in moisture content and drying rates.	Atmospheric environmental and moisture conditions, local temperatures.	Not applicable	Not applicable	Not applicable	Fire behavior indexes representing rate of spread, fuel weight consumed, and fire intensity.	Consideration of FFMC, DMC, DC.
Stocks et al. [13]	Local weather data, fuel moisture, dry-bulb temperature, relative humidity, wind speed, cumulated precipitation	Not applicable	Not applicable	Not applicable	Not applicable	Observation of fire behaviour from point-source weather measurement via CFFDRS.	Fire danger prediction mapping.

Sayad et al. [27]	Information was acquired from The Canadian Wild-land Fire Information System (CWFIS)	Not applicable	Not applicable	Not applicable	Not applicable	Not applicable	Neural Networks and SVM

DETECTION AND RESPONSE MODELS

Forests play a vital role in maintaining the Earth's ecological balance. Unfortunately, forest fires are typically detected only after they have already spread over extensive areas, making their containment and extinguishment exceptionally challenging, if not impossible. The outcome is a devastating loss and irreparable harm to the environment and atmosphere. Forest fires are responsible for a substantial portion of carbon dioxide (CO_2) emissions (contributing to 30% of CO_2 in the atmosphere), leading to severe atmospheric pollution. [43] Furthermore, they result in significant ecological damage, releasing substantial amounts of smoke and CO_2 into the atmosphere. Forest fires also trigger a series of terrible consequences, including long-term impacts on local weather patterns, exacerbation of global warming, and the extinction of rare plant and animal species.

The challenge with forest fires lies in the fact that these forests are typically located in remote, unmanaged areas abundant with dry and highly flammable materials such as trees, parched wood, leaves, and more, all of which serve as potent fuel sources. These components create an ideal environment for the initial ignition of a fire and continue to fuel it during subsequent stages. Fire ignition can be triggered by various factors, including human activities such as smoking or outdoor cooking, as well as other natural causes. Once the ignition process commences, the combustible materials readily sustain the central fire point, causing it to grow larger and spread. This initial stage of ignition is often referred to as the "surface fire" stage. Subsequently, the fire can extend to nearby trees, escalating into a "crown fire" with increasingly higher flames. [43] At this juncture, the fire often becomes uncontrollable, resulting in extensive landscape damage that may persist for an extended period, contingent upon prevailing weather conditions and the terrain.

Every year, vast areas of forests fall victim to destructive wildfires. These fire-ravaged areas emit more carbon monoxide than the collective emissions from all the vehicles on the road. Monitoring potential risk zones and early detection not only significantly reduce response times but also mitigate potential damage and firefighting costs. Following established guidelines, it takes 1 minute for a fire to consume as much as a cup of water, 2 minutes for 100 liters of water, and 10 minutes for a staggering 1,000 liters of water. [43] Therefore, the primary objective is to detect fires as rapidly as possible, pinpoint their exact locations, and promptly notify firefighting units. This deficiency is precisely what the present invention aims to address: detecting forest fires at their earliest stages, ensuring an increased likelihood of extinguishing them before they spiral out of control or inflict substantial harm.

Various detection and surveillance systems are deployed by authorities to safeguard against wildfires. These encompass human observers, whether in the form of ground patrols or stationed in monitoring towers, along with aerial and satellite surveillance methods. Additionally, there is a growing emphasis on employing advanced detection and monitoring systems that rely on optical camera sensors, various sensor types, or a fusion of multiple sensor technologies.

The most frequently used fire detection and suppression techniques employed by authorities can be summarised as follows: controlled burning, fire weather forecasts and estimates of fuel and moisture, watch towers, optical smoke detection, lightning detectors which detect the coordinates of the strike, IR, spotter planes, water tankers, and mobile/smartphone calls becoming increasingly common for detecting fires early. [43] Detection and monitoring systems are divided into the following two basic groups: volunteer reporting-public reporting of fires, public aircraft, and ground-based field staff, operational detection systems: fire towers, aerial patrols, electronic lightning detectors, and automatic detection systems. [43]

Fire suppression techniques encompass a range of approaches. For example, one method involves controlled burns in dry regions under the supervision of firefighters to prevent future crises. In Canada, water tankers deployed from aircraft are utilized, while in some Middle Eastern areas, a tactic involves clearing extensive swathes to create a firebreak and isolate the fire from fuel sources. In parts of Australia, fires are left to burn without intervention, provided they pose no threat to human safety or property, until they naturally extinguish.

Therefore, this subsection elaborates on the detection and response models. In particular, these models are separated into six subcategories: (a) fire detection, (b) fuels characterisation, (c) fire susceptibility mapping, (d) landscape controls on fire, and (e) fire behaviour prediction. For each subcategory, relevant works are investigated, highlighting how they can influence the TREEADS models. Table 2 summarises these models in terms of weather data, fire and smoke detection methods, environmental management, fuel consumption, fire spread rate, response management and methods.

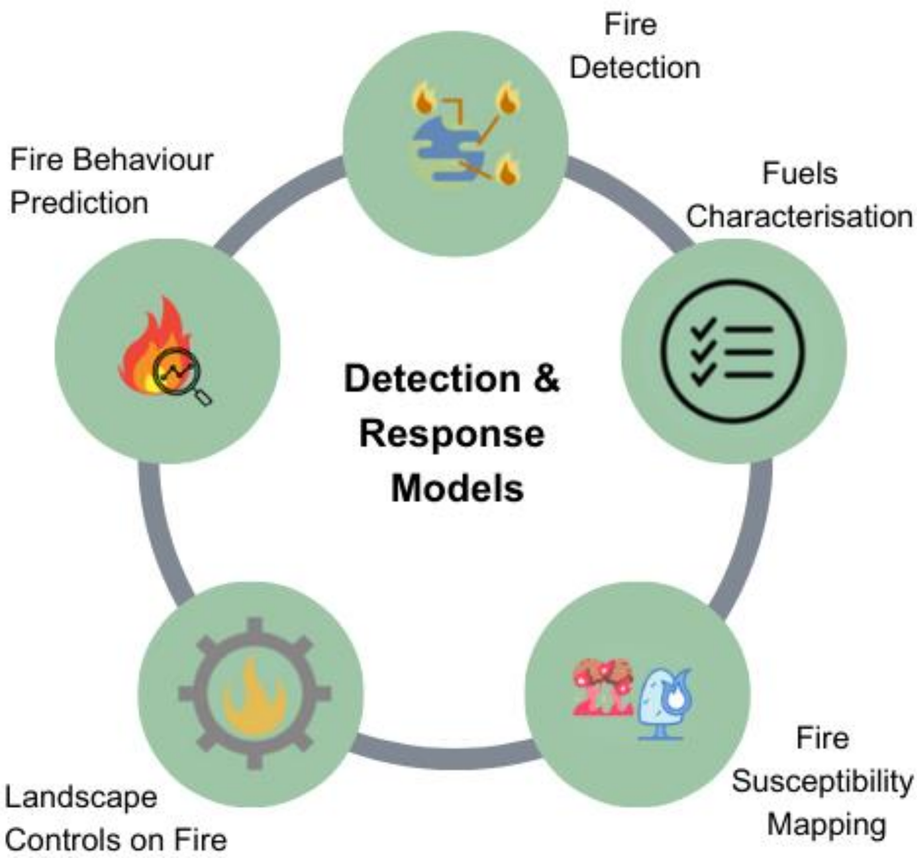

Figure 4 Sub-categories of Detection and Response Models

FIRE DETECTION AND RESPONSE

Timely wildfire detection prior to the ignition is fundamental to facilitating a quick and effective response. Traditionally, fires have been detected by human observers, by distinguishing smoke in the field of view directly from a fire tower, or from a video feed from a tower, aircraft, or the ground. All of the aforementioned methods can be limited by spatial or temporal coverage, human error, the presence of smoke from other fires and by hours of daylight. Automated detection of heat signatures or smoke in infrared or optical images can extend the spatial and temporal coverage of detection, the detection efficiency in smoky conditions, and remove bias associated with human observation. The analytical task can be described as a classification problem that is compatible with ML methods. More specifically, wildfire response issues have also been examined using ML techniques.

For example, Costafreda-Aumedes et al. [44] used ANNs to model the relationships among daily fire load, fire duration, fire type, fire size, and response time, as well as personnel and terrestrial and (or) aerial units deployed for individual wildfires in Spain. Most of the models in [44] highlighted the positive correlation of burned area and fire duration with the number of resources assigned to each fire, and some highlighted the negative influence of daily fire load. Rodrigues et al. modelled the probability that wildfire will escape initial attack using a RF model trained with fire location, detection time, arrival time, weather, fuel types, and available resources data. Important variables in Rodrigues et al. included fire weather and simultaneity of events. Julian and Kochenderfer [45] used two different RL algorithms to develop a system for autonomous control of one or more aircraft to monitor active wildfires.

In [44], Costafreda-Aumedes et al. successfully deployed ANNs in order to model regional patterns of firefighting resource deployment in Spain. The authors developed a model that suggests that Spanish agencies generally respond to large fires by adding more resources as the fires grow either in size or duration, but in some topical multiple-fire situations redirect resources from their use on large fires. However, national-level analyses may mask the fact that trends of regional fire-fighting resources differ across Spain. Efficiency can be improved by training decision-makers on advanced analysis of fire behaviour and meteorology, but in the future, it is expected to cause worse danger conditions, a more complex WUI environment and constrained budgets. The full suppression policy being enforced should be re-evaluated. The current pattern of just adding suppression resources with extended fire duration or size will not be the solution for future fire control, thus fire prevention should be a priority for Spain.

Modeling initial attack success of wildfire suppression in Catalonia, Spain [46]. In southern European regions, the scarce fires that escape initial attack are responsible for larger areas burned. Despite this fact, limited effort has been aimed to create spatiotemporal models addressing improving prepositioning and deployment of fire-fighting brigades on the first dispatch. To this end, the authors developed a model to assess the probability of containment of the fire by initial attack in Catalonia. The proposed model was trained using ML algorithms from georeferenced historical fire ignition locations, fire response and weather conditions. The results presented showed that early detection, ground accessibility, and aerial support governed the broad spatial pattern of fire containment probability, with strong gradients that encompass the lowest chances of containment in north-western mountains to the highest in the coastal belt. In turn, weather conditions and fire simultaneity were critical to defining the disparities during wildfire season. It was also found that fires igniting above the 85th percentile of temperature and wind speed, during simultaneous fire episodes at 12.5 km away from the nearest fire station will likely escape initial attack, and cause large events. The aforementioned hazardous fire danger conditions were observed 13 days per year on average during the period 1998–2015, with 5 fire simultaneous episodes escaping IA that burned 1546 ha in total. The results replicated the most typical weather and fire occurrence scenarios that first responders are likely to face during the wildfire season. This study reveals existing limitations in the prevalent fire exclusion policy of Mediterranean areas and promotes a comprehensive long-term wildfire management solution. This model may help inform science-based decision-making on IA and general fire response planning in the study area.

The contribution of this [45] work is to use images gathered from the wildfires to directly generate real-time bank angle commands to guide the aircraft around the wildfire as it expands. This method ranges to multiple aircraft and permits them to efficiently work together to monitor the wildfire growth. The authors presented a real-time guidance system for multiple fixed-wing aircraft to autonomously monitor wildfires. Given only sensor information, a deep neural network is trained to maximise wildfire surveillance for pairs of aircraft. In this study, two different approaches to this problem were developed and compared, which found that the neural network controller is able to accurately guide the aircraft along the firefront. The trained network could be incorporated into the onboard guidance systems of real aircraft to generate intelligent flight trajectories for monitoring wildfires.

Furthermore, Arrue et al. [47] applied ANNs for infrared (IR) image processing to detect true wildfires. Several researchers have similarly utilised ANNs for fire detection. Furthermore, Liu et al. applied ANNs on WSNs to build a fire detection system, where multi-criteria detection was applied to various attributes such as flame, heat, light, and radiation; to detect and raise alarms. Other ML methods used in fire detection systems include SVM to automatically detect wildfires from video frames, GA for multi-objective optimisation of a LiDAR-based fire detection system, and BN in a vision-based early fire detection system, ANFIS, and KM. CNNs are able to extract features and patterns from spatial images and are finding widespread use in object detection tasks and have recently been applied to the problem of fire detection. Various of these models were trained on terrestrial-based images of fire and/or smoke. Of particular note, Zhang et al. [48] found CNNs outperformed an SVM-based method and Barmpoutis et al. [49] found a Faster region-based CNN outperformed another CNN based on YOLO. Li et al. [50] applied a 3D CNN to incorporate both spatial and temporal information and in order to treat smoke detection as a segmentation problem for video images. Another approach by Cao et al. utilised convolutional layers as part of a Long Short-Term Memory (LSTM) Neural network for smoke detection from a sequence of images such as a video feed. They found the LSTM method achieved 97.8% accuracy, a 4.4% improvement over a single image-based deep learning method. Perhaps of greater utility for fire management were fire/smoke detection models trained on either UAV images or satellite imagery including GOES-16 and MODIS. Zhao et al. [51] compared SVM, ANN and 3 CNN models and found their 15-layer CNN performed best with an accuracy of 98%. In contrast, the SVM-based method was unable to extract spatial features and had achieved an accuracy of 43%. Alexandrov et al. [52]

found YOLO was both faster and more accurate than a region-based CNN method in contrast to Barmpoutis et al. [49].

In [47], an intelligent system for false alarm reduction in infrared forest-fire detection was created. Forest fires often are the cause of many environmental disasters, creating economical and ecological damage as well as endangering people's lives. An increased interest in automatic surveillance and early forest-fire detection has taken precedence over traditional human surveillance due to the latter's subjectivity affecting detection reliability, which is the main issue for forest-fire detection systems. The tedious process in current systems of the human operators required manually validating many false alarms. The authors propose the False Alarm Reduction (FAR) system, an alternative real-time infrared–visual system that can overcome this problem. The FAR system is consisted of new infrared-image processing techniques and ANNs, utilising additional information from meteorological sensors and from a geographical information database, taking advantage of the information redundancy from visual and infrared cameras through a matching process, and designing a fuzzy expert rule base to develop a decision function. Moreover, the system produces new software tools to verify alarms to the human operators.

A forest fire is considered a severe threat to forest resources and human life. Therefore, in [53] Liu et al. proposed a forest fire detection system that has an ANN algorithm implemented in a WSN. The proposed detection system mitigates the threat of forest fires by providing accurate fire alarms with low maintenance costs. The utilisation of novel multicriteria detection increased the accuracy, stated as an alarm decision depending on multiple attributes of a forest fire. An ANN algorithm is applied to fuse sensing data that corresponds to multiple attributes of a forest fire into an alarm decision. The introduction of the proposed system as well as a prototype comprising TelosB sensor nodes and a solar battery to power the WSN. To power the sensor nodes in the forest where only intermittent sunlight is available, the authors also developed a prototype of the proposed system comprising a solar battery module, fire detection module, and user interface module.

In [54], Zhao et al. proposed an automatic forest fire detection from video. Based on the 3D point cloud of the collected sample fire pixels, a Gaussian mixture model was created to help segment some possible flame regions in a single image. Then the new specific flame pattern is characterised by the forest, and three types of fire colours are labelled accordingly. With 11 static features containing colour distributions, texture parameters and shape roundness, the static SVM classifier is applied and filters the segmented results. Utilising defined overlapping degrees and varying degrees; the remained candidate regions are paired among consecutive frames. Subsequently, the variations of colour, texture, roundness, area, and contour are evaluated and then the average and the mean square deviation of them are obtained. Together with the flickering frequency from temporal wavelet-based Fourier descriptors analysis of flame contour, 27 dynamic features are applied to train the dynamic SVM classifier, which is utilised for the final decision. The aforementioned approach has been evaluated with dozens of video clips, and it can detect forest fire while recognising fire-like objects, such as red houses, bright lights and flying flags. Except for the acceptable accuracy, the detection algorithm performs in real-time, which proves its value for computer vision-based forest fire surveillance.

False alarm rates are often high due to natural objects, which have the same characteristics as flame, large variations of flame appearance and environmental changes that complicate fire detection including clouds, sun and light reflections. Therefore, the challenge in fire detection from digital images exists in the modelling and detection of the chaotic and complex nature of the fire phenomenon. Therefore, the authors in [49] proposed an efficient approach for early fire detection from images by combining a powerful deep learning technique with multi-dimensional texture analysis using Linear Dynamical Systems (LDS). At first the candidate fire regions of each image were extracted using a faster R-CNN network (experiments were performed applying three different architectures, namely AlexNet, VGG16 and Resnet101), each representing the candidate fire regions of an image as a cloud of points on the Grassmann manifold and finally extract a VLAD descriptor for each image. To evaluate the efficiency of the proposed methodology, images from two different databases containing a large number of images of wildfire were utilised, including images with dominant fire-like colours and/or fire-coloured objects. Specifically, annotated wildfire images were used from the Corsican Fire Database (CFDB) as well as images of various objects and classes from the PASCAL Visual Object Classes (VOC) dataset.

In [48], the authors utilised faster R-CNN to detect smoke in the forest. As available forest fire smoke images for training deep models are limited in scale and diversity, synthetic forest smoke images were produced by inserting two kinds of smoke, real smoke and simulative smoke, into the forest background. The results of the test by real forest smoke images prove the feasibility of this solution. It not only solves the problem of data lack but also eliminates the work of sample labelling. For the two smoke generation methods, although the images produced by the second method that inserts simulative smoke into the forest background are not visually realistic, the performance is better. The possible reason is that the smoke location provided by the second method is more accurate compared with the first method. It may be possible to further boost the performance by improving the synthetic process of forest smoke images or considering extending this solution to video sequences.

The purpose of this paper [50] is to facilitate the design of a system that monitors the great areas of mountainous terrain and forest areas in real-time. Ultimately, the authors propose a framework capable of functioning in the natural scene and detecting smoke timely in the case of a wildfire. As it is of utmost importance to minimise the severe impact of wildfires, this work places focus on detection sensitivity and achieving low false positive rates for the proposed wildfire detection system. Consequently, in order to meet the aforementioned requirements mentioned above, the authors propose a 3D-PFCN leveraging pyramid classification. The proposed 3D classification framework is at its core, a pixel-level segmentation neural network, which is capable of extracting a set of Spatio-temporal features, whilst supporting classification with a pyramid structure. The proposed classification framework managed to detect the presence of smoke accurately and in a timely manner in real-life tests, using a similar environmental scene as utilised in training data, which corresponds to a substantially complex natural environment.

In this study [55]., the authors propose an ABi-LSTM for early forest smoke recognition. Specifically, the proposed approach can be summarised as three parts: a) an Inception V3 network which is used to extract spatial features from smoke candidate patch step by step; b) a BiLSTM model which is designed to extract temporal features from forward and backward order by feed spatial feature of single patch; c) attention network is employed to optimise classification process with a soft attention mechanism that can automatically evaluate the importance of different frames. Extensive experiment results show that the proposed ABi-LSTM framework obtains higher accuracy in early forest fire smoke recognition compared with other methods. Moreover, an ablation study is conducted to evaluate the performance of each sub-model in ABi-LSTM. The proposed ABi-LSTM has been influenced by the attention mechanism in neural machine translation, which can adaptively focus on discriminative frames. As a result, this framework may be suitable for early forest fire smoke detection.

The main goal of the authors in [52] was to compare ML methods utilised for wildfire monitoring tasks. The research focuses on ML methods, including deep learning methods because artificial intelligence methods have better applications for real-time monitoring tasks. The advantages of ML methods against classical image processing methods utilised for monitoring were clearly defined in the study. The article considers classical methods of ML and deep learning methods such as Haar and LBP cascades, Faster R-CNN, SSD, and YOLO. Moreover, the authors compared various methods for aerial detection of wildfires. The comparison parameters applied during their method were the accuracy of the detection and the performance. The results depict that the best performance is achieved for classical methods of ML, however, their accuracy is lower than Faster R-CNN and YOLO models. The SSD model showed the worst performance results and similar accuracy results to classical methods. The results of smoke detection using Faster R-CNN show that the method's average performance is 4 FPS, at that only smoke with a light colour shade is detected. The YOLO model performed with the best accuracy among all considered models and was the fastest among deep learning models. Like Faster R-CNN, YOLO is more suitable for detecting fires at an early stage. Therefore, this model is optimal for solving monitoring problems.

In [56], Phan et al. aim to develop an autonomous and intelligent system built on top of imagery data streams, which are available from around-the-clock satellites, to monitor and prevent fire hazards from becoming disasters. Although, satellite data pose unique challenges for image processing techniques, including temporal dependencies across time steps, the complexity of spectral channels, and adversarial conditions such as cloud and illumination. The authors presented a novel wildfire detection method that utilises satellite images in an advanced deep learning architecture for locating wildfires at the pixel level. The detection outputs are further visualised in an interactive dashboard that allows wildfire mitigation specialists to deeply analyse regions of interest on the world map. The proposed system is built and tested on the GOES-16 streaming data source. Empirical evaluations show the superior performance of this approach over the baselines with a 94% F1- score and 1.5 times faster detections as well as its robustness against different types of wildfires and adversarial conditions.

SmokeNet: Satellite Smoke Scene Detection Using Convolutional Neural Network with Spatial and Channel-Wise Attention was introduced in [57]. A variety of environmental analysis applications have been enhanced by the utilisation of satellite remote sensing. Smoke detection based on satellite imagery is fundamental for wildfire detection and monitoring. Although, the commonly applied smoke detection methods mainly focus on smoke discrimination from a few specific classes, which reduces their applicability in different regions of various classes. The authors proposed a new large-scale satellite imagery smoke detection benchmark based on Moderate Resolution Imaging Spectroradiometer data, namely USTC_SmokeRS, consisting of 6225 satellite images from six classes: cloud, dust, haze, land, seaside, and smoke, as well as covering various areas of the world. Therefore, a new CNN model, SmokeNet, was introduced which incorporates spatial and channel-wise attention in CNN to impro feature representation for scene classification. The experimental results of the method using different proportions (16%, 32%, 48%, and 64%) of training images reveal that the proposed model performs better than other approaches with higher accuracy and Kappa coefficient. The proposed SmokeNet model trained with 64% training images achieves the highest accuracy value of 92.75% and Kappa coefficient of 0.9130. The model trained with 16% training images can also enhance the classification accuracy and Kappa coefficient by at least 4.99% and 0.06, respectively, over other approaches.

An UAV armed with GPSs can implement direct georeferenced imagery, mapping an area with high resolution. So far, the foremost difficulty in wildfire image classification can be considered the lack of unified identification marks, the fire features of colour, shape, texture (smoke, flame, or both) and background can diverge significantly from one scene to another. The authors in [51] showed the effectiveness of using saliency detection and deep convolutional neural network in localisation and recognition of wildfire in aerial images. The saliency detection method is applied to locate the core fire areas and extract fire regions into multiple fire images. The proposed technique mitigated severe feature loss due to direct resizing. Also, this technique significantly improved the volume of the database. In this paper, a DCNN architecture named 'Fire_Net' was proposed. It obtained satisfactory classification results. The proposed architecture performance was improved in comparison to previous methods by achieving an overall accuracy of 98%. Moreover, 'Fire_Net' achieved an average processing speed of 41.5 ms per image for real-time wildfire detection. To depict its practical utility, Fire_Net was evaluated on 40 sampled images in wildfire news reports and all of them were accurately identified.

FUELS CHARECTERISATION

Fires set on fire fuel particles which with the ensuing heat transfer between particles by conduction, radiation, and convection. As a result, the fire behaviour such as the fuel consumption, the spread rate and the intensity can be affected by the properties of the live and dead vegetative fuels along with moisture content, biomass, and vertical and horizontal distribution. Fuel properties are a necessary input in all fire behaviour models, whether it is a categorical vegetation type, as in the Canadian FBP System, or as physical quantities in three-dimensional space (e.g., FIRETEC model). There are two different scales where research to predict fuel properties has been carried out: (i) regression applications to predict quantities like the crown biomass of single trees as easily quantified variables (e.g., height and diameter) and (ii) classification applications to map fuel type descriptors or fuel quantities on a landscape utilising visual interpretation of air photographs and interpretation of the spectral properties of remote sensing imagery. Although few studies have selected ML for wildfire fuel prediction, allowing for substantially more research in this area. In an early study, Riaño et al. [58] utilised an ANN to predict and map the EWT and DM of wet and dry leaf samples from 49 species of broadleaf plants setting the values of reflectance and transmittance in the Ispra region of Italy. García et al. employed SVM to classify LiDAR and multispectral data to map fuel types in Spain. Utilisation of CART, RF, and stochastic gradient boosting (SGB), an ensemble tree method that uses both boosting and bagging, for mapping forest fuel types in Italy and found that SGB had the highest overall accuracy.

In [59], Linn et al. developed in 1997 FIRETEC a coupled atmospheric/wildlife behaviour model based on the principles of conservation of mass, momentum and energy. FIRETEC is combined with the hydrodynamics model HIGRAD in order to simulate wildfires using a terrain-following three-dimensional finite volume grid. The authors aim is to illustrate the use of the combined HIGRAD/FIRETEC modelling system for the examination of wildfire behaviour. Five examples were presented of simulations performed with HILGRAD/FIRETEC in idealised situations as well as realistic conditions. The results of these simulations are not unexpected or novel but the use of a physics-based full-transport model to perform the simulations represents the initial development of a new avenue in landscape-scale wildfire modelling. The simplicity of these idealised simulations allows for the isolation of some of the physical relationships that cause the simulated fires to act the way they do.

Fuel moisture content (FMC) is one of the most common variables that drive fire danger. ANNs were evaluated to calculate FMC by estimating the two variables implicated, equivalent water thickness (EWT) and dry matter content (DM). DM was calculated for fresh and dry samples since water masks the DM absorption features on fresh samples. The authors in [58] utilised the LOPEX database. 60% of the samples were employed for the learning process in the network and the remaining ones for validation. EWT and DM on dry samples estimations were as effective as other methods evaluated on the same dataset, such as inversion of radiative transfer models. DM estimations on fresh samples using ANN ($r2 = 0.86$) improved substantially the results using inversion of radiative transfer models ($r2 = 0.38$).

In [60], Pierce et al. aimed to quantify spatial patterns of forest fuels across a large, heterogeneous landscape and evaluate the effectiveness of RF as an approach to modelling plot level canopy fuel loads and then predictively map those loads across LVNP, California, USA. The specific research objectives were (1) quantifying surface and canopy fuel loads across LVNP and determining how they vary according to topography and vegetation type, (2) mapping surface and canopy fuels by integrating plot-level data with topographic characteristics and LandSat data using RF regression, (3) comparing the characteristics of the canopy fuel maps with standard datasets on canopy fuels, (4) using the maps of canopy and surface fuels to predict fire behaviour and then comparing predicted fire behaviour with observed fire severity within the perimeter of a 1382 ha Wildfire Use fire that burned in 2004.

In [61], Riley et al. established that a modified RF approach is an expedient method for imputing forest plots to a set of target landscape grids. This method produces a seamless grid of tree data at the landscape level. The modified RF method presented significant relationships between the target gridded data and the imputed plot data for the response variables of forest cover (86 %), forest height (97 %), and existing vegetation group (84 %), an indication of high model accuracy. The high classification accuracy is one of the more advantageous assets of the RF method, along with its ability to utilise categorical as well as numerical variables. Due to the high accuracy, the output imputed forest plot data should perform well in a number of applications, including estimation of risk from wildfire to terrestrial carbon resources, and analysis of the impact of fuel treatments on fire sizes and landscape-level burn probability.

The k-NN, RF and SVM, ML algorithms are being utilised in [62] for calculating aboveground forest biomass with remote sensing datasets, and all are considered viable and accurate alternatives to the classic parametric Multiple linear regression (MLR) method. Furthermore, the usual sources of uncertainty associated with the accuracy of the aboveground biomass (AGB) estimations are caused by remote sensing data such as field measurement errors, plot location errors, errors in the individual tree biomass equations, and errors caused by geometrical and radiometric correction of remotely sensed data. The parameterisation of ML algorithms also has a pivotal influence on the final performance of the models. The choice of method used will largely depend on the user's capacity to carry out that parameterisation because the techniques (especially SVMs) are not easy to apply and require a certain degree of expertise. The authors' findings indicate that SVM is the best alternative for experts, whereas RF represents a balance between model accuracy and ease of use for non-experts although differences with k-NN could not be statistically demonstrated.

In [63], Garcia et al. demonstrated a methodology to map fuel types utilising LiDAR and multispectral data. The authors propose in the study a two-phase classification method in order to discriminate the fuel classes of the Prometheus classification system, which is adapted to the ecological characteristics of the European Mediterranean basin. Firstly, the main fuel groups were mapped, namely grass, shrub and tree, as well as non-fuel classes, therefore, SVM classification was utilised with the combination of LiDAR and multispectral data. The overall accuracy of this classification was 92.8 % with a kappa coefficient of 0.9. Secondly, the method is directed at discriminating additional fuel categories based on vertical information deduced from the LiDAR measurements. Decision rules were enforced to the output of the SVM classification established from the mean height of LiDAR returns and the vertical distribution of fuels, defined by the relative LiDAR point density in different height intervals. The final fuel type classification yielded an overall accuracy of 88.24 % with a kappa coefficient of 0.86. In the study, it was found that there is some confusion between fuel types 7such as dense tree cover presenting vertical continuity with understory vegetation and 5 such as trees with less than 30 % of shrub cover and in some areas covered by Holm oak, which showed low LiDAR pulses penetration so that the understory vegetation was not correctly sampled.

FIRE-SUSCEPTIBILITY MAPPING

A considerable number of references applied several ML algorithms to map wildfire susceptibility, corresponding to either the spatial probability or density of fire occurrence (or other measures of fire risk such as burn severity), although other terms such as fire vulnerability and risk have also been utilised. The current approach was to create a spatial fire-susceptibility model applying either remotely sensed or agency-reported fire data with some combination of landscape, climate, structural, and anthropogenic variables as explanatory variables. In general, the various modelling approaches used either a presence-only framework such as MaxEnt or a presence-absence framework such as BRT or RF.

Researchers in the framework of long-term fire risk assessment have implemented spatial and non-spatial non-parametric prediction models to discover complex relationships among wildfire variables. The main scope was to overcome the assumption of spatial stationarity in the relationship between the response variable and the predictors, assumed by the traditional regression techniques. In [64], the authors tested and compared the potential of the CART and Multivariate Adaptive Regression Splines (MARS) models in predicting fire occurrence at the local scale. The test was performed in the Arno River Basin, a fire-prone area located in the central part of Italy. Road network, topographic variables and population data were implemented to build up a fire prediction model using 1621 ignition points recorded during the period 1997-2003. The models produced two prediction maps slightly similar. From the utilisation of the two models for the prediction of fire occurrence in the framework of long-term fire risk assessment, it can be deduced that the CART model performs better in terms of prediction power. Furthermore, it outputs the detected homogenous fire risk management units, that can be useful to support wildfire planning actions. On the other hand, the MARS model can produce a smoothed prediction surface. The two models utilised the default parameters, therefore better performances could be found testing other setting parameters. The results were also useful to analyse the behaviour of each independent variable in the regression process. Previous work can confirm the positive relationship of the road variable when expressed in terms of road density. The application of x and y variables can provide spatial information to the models, nonetheless, they have to be utilised carefully since unforeseen results can be produced.

The purpose of this study [65] was to quantify the best land fire hazard map by assessment of various factors using data mining techniques such as ANN and binary logistic regression. The predictive accuracy of land fire hazard models was summarised using Receiver Operating Characteristic (ROC). The ROC curve was greater with the ANN model (AUC 87%) compared to the binary logistic regression model (AUC 81%), with better sensitivity and specificity. Results obtained using the ANN model showed variables related to human presence significantly described the variability of land fire frequency. In addition to this, the factors found to be important for their contribution to land fire hazards in the ANN method are annual precipitation and annual mean temperature in agreement with the presence/absence of land fires. Annual precipitation and annual mean temperature may tend to produce dry extreme conditions which can increase land fire hazards. The results also enhanced the relevance of the use of the topographic wetness index and slope variables as well as land cover, in predictive analysis of land fire hazards, which appeared to be more accurate in the prediction of land fire hazards in the Golestan province, Iran. The land cover also had a significant influence on ignition frequency and contributed substantially to explaining the variability of ignition patterns. It was argued in this study that the human impacts (e.g., land clearance) are a reasonable proxy for land fires in the study area and non-anthropogenic fire might be rare. The map of land fire hazards produced in this study can be used as basic information to assist forest managers in vulnerability assessment and mitigation planning. In this study, the land fire hazard assessment and mapping of Golestan Province as the most fire-prone area in Iran creates a pilot study toward detailed land fire hazards for determining what areas are more likely to experience land fire hazards throughout northeast Iran.

In [66], Bisquert et al. utilised LR and ANNs to create a fire danger model. Remote sensing variables (EVI and LST) were applied as input variables for monitoring vegetation status in combination with fire history variables. Various combinations of input variables were evaluated utilising the LR method. The combinations of variables with the best results were introduced in an ANN and the results obtained from both techniques were compared and evaluated. The best combination of input parameters found was the 8-day LST with fire history variables collected throughout a year. The LST was expected to be a key factor in fire danger because higher temperatures are linked to lower moisture content and these conditions facilitate the ignition of vegetation. The ANN depicted better accuracy and precision than LR. Finally, three fire danger levels were defined into classifications from the results of the neural network, with 14% fire frequency at the low-danger level, 25% at the medium level and 65% at the high level. Classifying the fire danger levels allows for obtaining fire danger maps that facilitate prevention and extinction tasks.

The EUMed region is the area of Europe with the highest fire incidence. Inside the region, fire density has an irregular distribution in space and time. The likelihood of a fire occurring is affected by the interactions between the physical and human variables that affect the ignition and spread of a fire. In this study [67], the probability of fire occurrence was modelled by applying two different methods: MLR and RF. The comparison of the results that occurred with these two methods allowed for the examination of non-linear relationships between the variables, not assumed in MLR, and the investigation of the potentialities of the RF method in fire occurrence modelling. Moreover, both methods ranked the variables according to their relative contribution to the model, allowing for the identification of the common factors in both models and, thus, intensifying their significance in explaining fire density distribution. The two models demonstrated distinct results; the RF model demonstrated higher predictive accuracy than LR, reflecting the existence of nonlinear trends. Furthermore, spatial autocorrelation in model residuals was minimised to a much higher degree with the RF model. Despite these differences, both models demonstrated north-western Iberia and southern Italy as areas with high fire density, while northern France, north-eastern Italy and northern Greece were detected as low fire density areas. Moreover, it was also possible to detect common significant variables, providing important insights to better understand the factors affecting fire occurrence in this region, during the fire season.

In various researches, human-induced ignition risk has been excluded from the fire danger models developed. Therefore, the authors in [68] depict that, by analysing historical data on fire ignition point locations, there is the ability to gain the necessary predictive capability, making it possible to quantify ignition probability in space. The analysis is performed by applying inductive methods in a raster GIS, and it explores the information contained in the spatial attributes of the phenomenon. The raster GIs database applied in the study contains a layer with the location of ignition events and a set of layers corresponding to potentially explanatory variables. This data set is analysed by applying genetic neural networks and LR. The LR is appropriate because the proposed model is a binary event (occurrence or absence of ignition] utilising multiple independent variables, and it has been applied successfully in similar studies. In this study, neural networks have been utilised to test whether non-linear, non-parametric methods can improve upon the results obtained with traditional statistical methods.

The region of Madrid represents an example of the socio-economic changes that occurred in relation to wildfire occurrence in the last decades throughout the European Mediterranean basin. By modelling wildfire occurrence in two separated periods, this study [69] explained wildfire occurrence by detecting these changes in the socio-economic drivers as part of the exodus from rural to urban areas. Predictors like pop, WUI and roads enhanced their relevance in the 2000s whereas FGI decreased dramatically for both models. Either model performed better wildfire occurrence detection in the 2000s than in the 1980s. Maxent model performed better than the GLM in both periods according to indicators like sensitivity or commission error. A steadier result assures the model replicability for other time periods that can help take preventive measures to manage wildfires in this region. For instance, assign extinction resources in areas with high predicted probabilities, especially those with high ecological value or socio-economic vulnerability.

This study [70] was designed to address two main issues: (1) first, to apply evaluation on the predictive capability of the fire spread pattern classification by means of correlative models in a Mediterranean region affected by large fires. Fires were classified in the field according to their dominant spread pattern, which is theoretically related to different combinations of weather, topography and vegetation (the fire behaviour triangle); (2) then attempt to assess the relative contribution of these environmental factors to each type of fire spread pattern with the aim of testing the hypothesis that each spread pattern is associated with specific combinations of these factors. According to the dominant mechanisms behind fire spread patterns, it was expected that convective fires would be more strongly related to forest structure descriptors, whereas wind-driven fires would be more strongly related to wind descriptors. It was also predicted that topography-driven fires are related to topographic factors, and they should occur over a broader range of environments where stronger fire spread determinants such as fuel loads or strong winds are not greatly inducing the occurrence of the other fire spread patterns because wind or high vegetation loads can overcome topography effects and transform an initially topography-driven fire into a convective or wind-driven fire. Consequently, topography-driven fires are more likely to occur under less specific situations where the other stronger drivers do not prevail.

In [71], the authors demonstrated that the BBN model can have high precision and capability in predicting wildfire incidence. Other influencing factors can be added or removed from this BBN model to improve its predicting ability. Performing relevant studies to analyse the interactions between wildfire incidence and more environmental and management factors can facilitate the updating process of the BBN model. The graphical interface of the BBN model facilitates communication about systems behaviour among managers and policymakers. Hence, they can organise and structure different sources of knowledge about the systems and assist stakeholders in making more informed decisions. The main aim of the developed fire risk assessment tool is to provide timely information regarding fire occurrence. It assists managers to prevent uncontrolled fire incidents or minimise hazards, especially in arid and semi-arid areas with relatively unknown consequences. The BBN modelling approach provides a tool for managers to identify the most sensitive areas to fire occurrence. The BBN modelling approach is highly complementary to current fire simulation models. This is due to the data needed for populating the probability tables of BBNs can come from a number of sources, with one of these being other fire simulation models. The reliability of a BBN model is affected greatly by the accuracy of its probability tables. Reliability can be researched by studying the robustness of the model, that is, by considering the extent to which deviations from the network's probability assessments influence the output. Sensitivity analysis can aid to assess the robustness of the fire BBN model. Both the predictive ability and ability to accommodate uncertainty are highly desirable features of the developed BBN model for predicting fire occurrence.

This study [72] is based on the notion of the differential temporal patterns of human-caused wildfires. It is important to comprehend that time (month, day of the week, etc.) is pivotal in the overall ignition probability, as well as in the factors that condition this probability. This is based on spatio-temporal dimensions of human activities, as these are affected by daily, weekly, monthly and seasonal cycles. The aim of this study is the generation of seasonal and day-type models that account for the differential spatio-temporal behaviour of human-related driving factors over wildfire ignition probability in northeast Spain. This work aims to move one step forward towards achieving more accurate predictions and ultimately developing more efficient dynamic predictive models. Therefore, a new methodological approach was created combining the dynamism of some fire drivers with the specific temporal variability of human activity. The novelty of the proposed design and application of the models is that it is based on specific scenarios of fire occurrence, presence-only methods (MaxEnt) and high-resolution spatial datasets to report for fire ignitions and human-related wildfire drivers. The performance of these dynamic models was evaluated against random background samples and through a comparison of their predictive capacity with static models using wildfire data from 2012. Overall, dynamic models perform better than the static methods, reporting AUC values consistently above 0.85 in comparison to the 0.7 observed in static models.

This study [73] confirmed that the fire regime in an alpine region has distinct patterns and causes depending on the ecosystem and the season involved. Anthropogenic drivers, from negligence-related reasons, were the most common causes of ignition, but the incidence of fires starting from lightning has been increasing. From a management point of view, the spatially explicit approach allows to carry out of spatially targeted fire management strategies and may be integrated into future fire management plans on a regional and local scale. Spatially explicit hazard assessments can support managers in carrying out appropriate preventive and pre-suppression activities, locating helicopter water points, planning fuel management interventions, parameterising fire behaviour and landscape dynamics models and simulating different fire scenarios with different fire-fighting tactics. Furthermore, by combining the fire danger with the vulnerability to fire, a cell-by-cell assessment of the resulting fire risk can be carried out. Therefore, in less vulnerable areas the strict fire suppression method may be reconsidered, and fires allowed to burn a certain share of the land to restore historical disturbance regimes and enhance the functionality of those forest ecosystems that evolved with fire. From the point of view of the drivers of fire ignition, the importance of urban areas and roads are highlighted as potential sources of ignition, policies that regulate development in the urban-wildland interface, and possibly hazardous human activities near hotspot fire locations and during periods of high weather risk. Under the current scenarios of climate change and more frequent drought and lightning, silvicultural prevention should be done more frequently to minimise the load and continuity of forest fuels for an effective reduction of wildfire risk.

In [74], the authors investigated five models; the RF-cost sensitive analysis was the best method for predicting wildfire ignition susceptibility. The RF-cost sensitive analysis had the highest accuracy (88.47%) for all of the samples, and 94.23% accuracy for wildfire ignition prediction in Yunnan. In comparison with the widely utilised GLM models (LR and probit regression models) and the ANN, the RF-original model enhanced the total accuracy by 22.23, 22.48, and 9.56%, respectively, and the wildfire ignition prediction by 16.63, 16.03, and 10.45%, respectively. Wildfire susceptibility can be evaluated by applying various models, which range from conventional regressions to more recently generated machine-learning models. Careful processing of data samples is required, however, to resolve issues of data imbalance and to avoid potentially misleading results due to the overwhelmingly large number of non-ignition samples. High sensitivity should occur for good ignition prediction, the specificity and accuracy factors should also be considered. However, the performance of machine-learning methods (the ANN and RF models) evaluated in this study was better than that of the logistic and probit regressions, the numbers of layers in the ANN and trees in the RF should be further tested to achieve optimised results.

Wildland fire is a major process concerning forests of the western United States (US). Variation in fire behaviour, which is heavily influenced by fuel loading, terrain, weather, and vegetation type, leads to heterogeneity in fire severity across landscapes. The authors in [75] explored the drivers of high-severity fire for forested ecoregions in the western US over the period 2002–2015. Fire severity was quantified by utilising a satellite-inferred index of severity, the relativised burn ratio. For each ecoregion, BRT were applied to model high-severity fire as a function of live fuel, topography, climate, and fire weather. It was found that live fuel, on average, was the most important factor driving high-severity fire among ecoregions (average relative influence = 53.1%) and was the most important factor in 14 of 19 ecoregions. Fire weather was the second most prevalent factor among ecoregions (average relative influence = 22.9%) and was the most critical factor in five ecoregions. Climate (13.7%) and topography (10.3%) were less influential. The probability of a high-severity fire was predicted where a fire occurs, using recent (2016) satellite imagery to characterise live fuel for a subset of ecoregions in which the model skill was deemed acceptable (n = 13). These ecoregional maps provide relevant and up-to-date information for scientists and managers who are tasked with managing fuel and wildland fires. Lastly, an example of the predicted likelihood of high-severity fire under moderate and extreme fire weather before and after fuel reduction treatments was provided to show how the framework and model predictions can potentially act as a performance metric for land management agencies tasked with reducing hazardous fuel across large landscapes.

Mapping the spatial prediction of wildfire susceptibility is a major component of emergency land management, wildfire prevention, the mitigation of fire impacts by on-time responses and recovery management. Wildfire susceptibility maps have often been used to prioritise investments in the prevention of this hazard. Although, applying different methodologies can result in different susceptibility maps with a range of accuracies. Therefore, the effectiveness of each approach, in particular, the more common ones, should be evaluated. The authors in [76] applied three different ML approaches, namely those of the ANN, SVM and RF, that were trained with the MODIS hotspots through a four-fold CV. The ML methods were created and trained based on the previous wildfire events between 2012 and 2017, as well as the factors affecting the wildfires. The performances of the methods were tested by the ROC curve, and the importance of each condition factor was evaluated using a sensitivity analysis. Though a different resulting spatial prediction of wildfire susceptibility maps occurred, most of them revealed that the central, east, southern and northern regions of this study area are more susceptible to wildfires. As the most relevant conditioning factors regarding wildfire and the more common ML approaches were applied, the performed workflow can easily be generalised and adapted to different locations like California, Australia, and Spain, i.e., fire-prone regions. Therefore, the transferability of the workflow requires minor changes and localisation in related conditioning factors.

Many countries have detailed programs for forest fire protection, which are founded on prevention and fire-fighting measures. A fire detection system is one of the most fundamental aspects of forest fire protection before the fire spreads over larger areas. Therefore, the main purpose of this research [77] was to depict the results of an ensemble learning method applying a Bayesian average based on predictive results from the SVM and RF methods. The authors modelled and predicted suitable locations for the outbreak of forest fires utilising ML algorithms. Regional forest fire modelling is a regular, nonlinear and complex issue that cannot be easily evaluated and predicted. In the current research, the results of forest fire susceptibility maps were compared by utilising supervised and versatile ML algorithms (SVM and RF) and their ensemble in the Tara National Park, Serbia. Based on the occurred AUC, all models had the most scientifically satisfactory reliability and could be applied at the regional level for forest fire susceptibility mapping. The results demonstrated that the ensemble model using the Bayesian average outperformed the others.

In [78], the authors applied three ML/data mining approaches for forest fire susceptibility mapping from a set of topographical, metrological, and geological features. The forest fire occurrence of Minudasht Township, Golestan Province, Iran, was applied to prepare and validate the difference between the mentioned ML models. The BRT, GAM, and RF were utilised to discriminate between the absence or presence of forest fire, with performances peaking at AUC of 0.8084, 0.8770, and 0.7279, respectively. The ML algorithms were applied to perform feature selection in order to reveal the variables which affect most in determining the spatial distribution of forest fire. The findings from BRT, GAM, and RF highlighted that annual rainfall, slope degree, distance to roads, land use and annual temperature were the more effective factors in forest fire occurrence. This study found that the GAM model could be more useful in forest fire occurrence and mapping in comparison with BRT and RF models. Furthermore, these methods show the most important features to be selected. In final conclusion, the results of this study can be applied to early warning, fire suppression resource planning and allocation of works. The results obtained from this study provide a considerable contribution to the forest fire literature. The proposed models can be further improved using other forest types, tree composition, and CC percentage factors. In total, the authors couldn't use the same variables in different regions because forest fire in each part of the earth has its own characteristics. By the way, the mentioned models could be compared with other data mining models including CART, MARS, ANN, and SVM, and their results considered in this area and other areas.

This research [79] introduced and verified a new hybrid ML approach LogitBoost ensemble-based decision tree (LEDT) integrating LogitBoost ensemble and decision tree and applying it to forest fire susceptibility mapping with a case study at Lao Cai Province in the Northwestern region of Vietnam. According to current literature, LEDT has not been explored for forest fire susceptibility modelling. The GIS database, which was developed with 257 fire locations and ten forest conditioning factors, was applied to train and validate the proposed model. To derive the forest fire susceptibility index, the LEDT was formulated as a pattern recognition model that predicts the pixels of the study area to the two classes, forest fire and non-forest fire. Experimental outcomes show the high performance of the proposed model, demonstrating that the LEDT is capable to predict forest fire susceptible areas with high accuracy, which contributes to more trusty planning and management of prevention. The main advantage of the LEDT in comparison with other ML techniques is that no sophisticated optimisation is required. However, the performance of the LEDT model is influenced by the number of tree-based classifiers used; therefore, a trial-and-error test is required. Compared to benchmarks, RF, SVM, and KLR, the performance of the LEDT model was superior, due to the fact that the LEDT model focused on processing misclassified pixels in the fire susceptibility modelling by increasing the weights of these misclassified pixels and decreasing the weights of the correct classified pixels. Consequently, the model works better with uncertainty data, a critical issue in forest fire susceptibility mapping because the data are often from different sources and at different resolutions. In addition, the LogitBoost ensemble can handle noise data due to the use of a diversity of the decision tree-based classifiers; the LEDT model is more robust and accurate than the benchmarks. These facts indicate that the LEDT is a new valid tool for forest fire susceptibility mapping. In conclusion, this research may assist other scientists in developing susceptibility maps for other areas, as well as provide an approach applicable to geo-environmental issues other than forest fire assessments.

In [80], the authors researched a CNN with deep architectures for the spatial prediction of forest fire susceptibility in Yunnan Province, China. Past forest fire locations from 2002 to 2010 were extracted and a set of 14 forest fire influencing factors were optimised by applying multicollinearity analysis and the IGR technique. Pre-processing methods were applied for forest fire affecting factors and the methods for creating effective training sample libraries. The CNN architecture suitable for the prediction of forest fire susceptibility was designed, and the hyperparameters were optimised to improve the prediction accuracy. Several common methods, such as more training samples, regularisation, batch normalisation and reduced architecture complexity, were applied in the CNN model to prevent overfitting. Afterwards, the test dataset was utilised in the trained model and the prediction map of ignition probabilities was generated by the CNN model. The performance of the proposed model was compared against traditional ML methods utilising several statistical measures, including WSRT, ROC, and AUC. The CNN model (AUC = 0.86) has better predictive power in comparison to the benchmark methods according to the ROC–AUC. The probability result generated by the CNN can distinguish the very high and very low susceptible zones, and the susceptibility spatial pattern was very distinct. The CNN model shows a strong generalisation ability with a short prediction time when using GPU-accelerated computing technology.

LANDSCAPE CONTROLS ON FIRE

The applications of ML methods in studies of burned-area prediction have only become common relatively recently compared with other wildfire domains, yet already several studies incorporated a variety of ML methods. For example, Cheng and Wang [90] applied an RNN to forecast the annual average area burned in Canada, while Archibald et al. [91] utilised RF to evaluate the relative importance of human and climatic drivers of burnt areas in southern Africa.

Mayr et al. [92] evaluated five common statistical and ML methods for predicting burned area and fire occurrence in Namibia, including GLM, MARS, regression trees from recursive partitioning RF, and SVMs for regression. The RF model performed best for predicting burned areas and fire occurrence. Likewise, de Bem et al. [93] compared the application of LR and ANN for modelling burned areas in Brazil. Both LR and ANN showed similar performance; however, the ANN had better accuracy when identifying non-burned areas but displayed lower accuracy when classifying burned areas.

In [81], Cheng and Wang presented an application of spatio-temporal data mining for forest fire prevention. The research paid special attention to the spatio-temporal forecasting of a forest fire. An improved spatio-temporal integrated forecasting framework – ISTFF – was proposed, and its use was illustrated by a case study of forest fire area prediction in Canada. Comparative analysis of ISTFF with ARIMA and STIFF showed the high prediction accuracy of ISTFF. The enhanced accuracy of ISTFF is impacted by the introduction of the Elman neural network for spatial forecasting. This is a recurrent dynamic neural network that can recognise the states of the input and the states between the input and the output and is suitable for modelling dynamic change in forest fire over space. Another contribution of this research is the incorporation of the spatial association of the spatial components in the initialisation of the structure and weights for the Elman network. The effect of spatial correlation on the accuracy of spatio-temporal forecasting was explored when utilising a neural network for spatial forecasting. The Integrated Spatio-temporal Data Mining for Forest Fire Prediction case study demonstrates that, if there exists a stronger spatial correlation between target subcomponent and non-target subcomponents, ISTFF can obtain better prediction performance. On the other hand, if the spatial autocorrelation between the target subcomponent and non-target subcomponents is irrelevant, then ARIMA is much better than ISTFF. Despite its promising performance, ISTFF handled only one variable in the proposed case study. When the forecasting of one variable is dependent on other variables, the correlation between different variables should be taken into consideration. The integrated spatio-temporal data mining framework allows the data stored in the forest fire information system to be fully assimilated and manipulated for fire prediction and prevention. The methodology developed in this study will improve the prediction of spatiotemporal processes in other application domains, such as meteorological studies.

The factors regulating the extent of fire in Africa south of the equator were researched in [82] applying moderate resolution (500 m) satellite-derived burned area maps and spatial data on the environmental factors thought to affect the burnt area. A RF regression tree procedure was utilised to find the relative importance of each factor in explaining the burned area fraction and to address hypotheses concerned with human and climatic effects on the drivers of burnt area. The model depicted 68% of the variance in the burnt areas. The best predictors were tree cover, rainfall in the previous 2 years, and rainfall seasonality. Human activities were also demonstrated to influence the burnt area. The analysis showed no indication that ignitions were limiting the total burnt area on the continent, and most of the spatial variation was due to variation in fuel load and moisture.

This study presents insights into the physical, climatic, and human drivers of fire and their relative importance across southern Africa, and demonstrates the beginnings of a predictive framework for the burnt area.

In [83], the authors have confirmed the fuel limitation of arid ecosystems. Based on a 16-year record (April 2000-March 2016) derived from the MODIS Burned Area product (MCD45A1) and a large set of environmental and human-related predictors, the controls of two main fire regime parameters in Namibia were evaluated, namely Burned Area (BA) and Fire Occurrence (FO). The predictive performance of five common statistical and ML techniques were examined and the effects of spatial autocorrelation were considered. Machine-learning techniques enhanced the predictions of BA and FO, due to their ability to detect complex non-linear interactions. Where model performances generally decreased with the consideration of spatial effects and even demonstrated indications of proportionality. The exceptional importance of average precipitation for fire activity across Namibia was highlighted. Precipitation indirectly controls fire activity by productivity and, thus, by the availability of (surface) fuels. In the RF models which performed best according to the Root Mean Square Error, both fire regime parameters were predicted to increase above an approximate threshold of 400 mm. A certain openness of the landscape, which was indicated by moderate levels of vegetation green-up, appeared to be beneficial to BA and, hence, the extent of fires. Human activities, such as the number of inhabitants and livestock amount, modify the biophysical determination of fire activity on smaller spatial scales as they additionally 'consume' fuels. Resultantly, consistent negative relationships were retrieved for both fire regime parameters. Although smaller and lower-intensity fires are largely missed with the MCD45A1 record and the non-stationarity of the relationships retrieved cannot be neglected, the above findings may facilitate a framework for effective and adaptive fire management in Namibia.

Predicting the spatial distribution of wildfires is an important step toward proper wildfire management. In [84], Pozzobon de Bem et al. utilised two data-mining models commonly applied to predict fire occurrence – LR and an ANN – to Brazil's Federal District, located inside the Brazilian Cerrado. Landsat-based burned area products were used to generate the dependent variable, and nine different anthropogenic and environmental factors as explanatory variables. The models were optimised via feature selection for the best AUC and then validated with real burn area data. The models had similar performance, but the ANN model showed better AUC (0.77) and accuracy values when evaluating exclusively non-burned areas (73.39%), whereas it had worse accuracy overall (66.55%) when distributing burned areas, in which LR performed better (65.24%). Moreover, the contribution of each variable was compared to the models, adding some insight into the main causes of wildfires in the region. The most critical aspects of the burned area distribution were land-use type and elevation. The results demonstrated good performance for both models tested. These studies are still uncommon despite the importance of the Brazilian savanna.

FIRE BEHAVIOUR PREDICTION

Fire behaviour consists of physical processes and characteristics at a variety of scales, incorporating combustion rate, flaming, smouldering residence time, fuel consumption, flame height, and flame depth nevertheless the papers include in this section deal mainly with larger-scale operations and characteristics such as the prediction of fire spread rates, fire growth, a burned area, and fire severity, conditional on the occurrence of one, or more, wildfires. On FBP the emphasis is on prognostic applications, in contrast to the problem domain in fuels characterisation and fire weather detection in which there is a concentration on diagnostic applications.

Predicting the spread of wildland fire is a crucial task for fire management agencies, especially to alleviate the deployment of suppression resources or to anticipate evacuations one or more days in advance. Therefore, a major number of models have been created using different approaches.

The ability to estimate, in some probabilistic sense, the future size of known fires, or the location of as yet unobserved fires, enables optimised tasking and/or routing of platform-based (satellites, UAVs) sensors. Optimising the allocation of sensors to wildfires to determine wildfire state, the more accurate the understanding of this state will be, which can lead to improved allocation of suppression assets and hazard monitoring and mitigation. The authors in [85] employed data mining techniques to predict which fires are likely to increase, or decrease, in size. The authors based their model on satellite observations to understand if such information is sufficient for real-time tracking of Earth phenomena related events, such as wildfires. Remote sensing data is ideal for this work as it allows for more complete observational coverage in space and time of key variables that are difficult to obtain via direct measurements from the field. The models used multiple years of archived data from the MODIS sensor combined with Landsat land cover data and NOAA weather observations. Acquiring and maintaining an accurate understanding of a wildfire's dynamic state, in terms of its location, type, and other characteristics, such as speed of propagation, combustible material, direction, topography, and weather effects, is central to being able to fight the fire in an efficient and timely manner.

Real-time forest fire spread forecasting is affected by time restrictions, resource management, and accuracy factors. In [86], Artés et al. depict a cyberinfrastructure for forest fire spread forecasting that incorporate input data gathered from various sources such as satellites and remote meteorological sensors. The information collected must be converged to fit simulation tools, which will leverage high-performance computing platforms and parallel programming paradigms to be able to output real-time results. The proposed system is founded on the Two-Stage prediction framework composed of two stages the Calibration stage and the Prediction stage. The calibration stage is established from a GA that adjusts the most sensitive parameters of a forest fire spread model by trying to reproduce the recent past as closely as possible. The GA uses as a fitness function, a spatial optimisation objective function, which tries to minimise the error between the observed real fire propagation and the spatial fire evolution provided by FARSITE. The calibration stage is time-consuming due to the iterative nature of the GA and the time spent on the simulations executed at each iteration. Therefore, to overcome this, a Time-Aware Classification (TAC) was combined in the calibration stage to determine the number of cores to allocate to each individual in the population taking into account the time constraints. Regardless of showing the TAC approach ensuring that simulations run within the allocated time, it can fall into local optima of the search space. The development of Re-TAC overcomes the time restriction by using rescaled coarse resolution data. The ReTAC method produces good results when dealing with large forest fires, while an accurate solution could be discarded in the TAC approach. Re-TAC significantly decreases the error in contrast with applying the TAC version, with accuracy closer to the single-core scheme where no time limit constraints are imposed. Re-TAC improves the prediction accuracy and time savings based on the computational capability. Henceforth, Re-TAC depends on high-performance computing platforms to exploit the two levels of parallelism. OpenMP pragmas have also been exploited to parallelise the execution of a single forest fire spread prediction. The Re-TAC Two-Stage prediction scheme has been validated to be successfully deployed as a fire forecasting aid to forest fire operations managers and analysts.

In [87], Houssami et al. 2018 conducted an experimental and numerical study to assess the performance of different sub-models and parameters used to describe the burning dynamics of wildfires. The authors suggested the necessity of detailed physics-based models to be studied, adding data regarding fuel and environmental characteristics (i.e. wind), outlining the necessity of establishing a framework tailored to the development of fire modelling with the multiphase approach. This methodology adopts a building block approach to model development and promotes a better understanding of forest fuel flammability and of its corresponding fire dynamics. This study incorporates well-documented fire experiments that are conducted in a controlled environment, providing precise measurements for different fuel and ambient conditions, to quantify the influence of the parameters on the models' numerical predictions. In this study, simulations were completed utilising ForestFire- FOAM (FFF). The authors validated the significance and the implications of using appropriate submodels, by comparing the different simulations and experiments, each with various fuel bulk densities and various inlet flows and they demonstrated which submodels need to be appropriately defined in order to provide acceptable predictions.

In [88], Denham et al. created an application for forest fire simulation and fitting to accomplish the aim to estimate the parameters involved in fire propagation and efficiently implement a parallel modular open-source computing tool. Determining stochastic fire propagation parameters and ignition points once a fire had occurred is of critical significance. Accessing this type of data to identify the more sensitive parameters it will aid the propagation of one or more fires and eventually predict fire propagation under different scenarios. The parallel cellular automata is a spatial stochastic model for fire propagation mounted on several layers that describe topography, fuel type, wind speed and direction, vegetation aspect and slope, that can be easily adapted to include other layers, as well as to implement different rules for fire propagation. With the proposed tool the fire-starting point can be estimated, allowing the analysis of mapped fires with unknown starting points. However, some of the propagation parameters lose identifiability when the coordinates of the ignition point are considered as an additional parameter. This could be probably improved either by fitting several fire scars instead of only one considering ignition points as nuisance parameters or by using an ensemble of several fitness functions to rank simulations. Fitting real fire maps to estimate propagation parameters and eventually fire ignition points and testing other functional dependencies of fire propagation probability is feasible through the utilisation of the tool. Additionally, it would be of interest to fit times of fuel consumption, a feature that will be also added to this application. Given that this tool is inherently parallel it could be eventually used for fire propagation prediction for which computing times should be the minimum possible simulation times.

In [89], Ascoli et al. developed a method to create and calibrate custom fuel models by associating the genetic algorithms (GA) to the Rothermel fire spread model. GA generates at random solutions of fuel model parameters to form an initial population. The validation of the solutions occurred against observations of the fire rate of spread. The population is chosen for its best members, crossed over and mutated within a range of model parameter values, until a satisfactory fitness is achieved. The authors demonstrated the improvements of GA to the performance of the Rothermel model in three published custom fuel models for litter, grass and shrub fuels where the root mean square error decreased by 39%, 19% and 26%. The authors utilised GA to calibrate a mixed-grass–shrub fuel model, applying fuel and fire behaviour data that occurred from fire experiments in dry heathlands of Southern Europe. The new model had decreased the prediction error against a validation dataset significantly, using standard fuel models built leveraging average values of inventoried fuels, and predictions of the Fuel Characteristics Classification System. GA validated a tool to calibrate fuel models and enhance the Rothermel model predictions. GA grants exploration of a continuous space of fuel parameters, making fuel model calibration computational effective and easily reproducible, and does not require fuel sampling.

In [90], Kozik et al. developed a software system for constructing a fire model, which ensures real-time simulation of fire evolution. The system allows interactive editing of the model; as a result, it is possible to check rapidly whether the firefighting measures such as forest devastation, digging of ditches and initiation of an opposing fire are effective. As the velocity of decision making and the quality of these decisions are critical factors in the firefighting procedure, the quality of traditional learning and learning with the use of the Kalman filtration are compared; the latter is demonstrated to ensure better convergence and stability of the learning process. Model experiments are performed for determining possible variants of fire evolution for different wind velocities and surface reliefs. In particular, it is demonstrated that the fire can overcome obstacles in the form of regions consisting of incombustible materials (e.g., ditches, rives) owing to the global character of connections of the neural network modelling the fire. The developed model can be effectively used for firefighting under conditions of continuous monitoring of fire evolution by means of aerial or satellite photographing of the fire region.

In forest fire spreading the quantitive simulation is an integral part of designing quick risk management and implementing effective suppression policies. The cellular automaton (CA) is one of the most widely utilised modelling approaches and has been used to simulate the complex mechanisms of fire spreading. Although the more common CA models, apply extensive studies on the physical principles of forest fires to define the local transition rules. In order not to define transition rules, the authors in [91], use Extreme Learning Machine (ELM), which is a very popular model for data-driven learning. In the modelling approach, the local evolution rules of fire spreading are given by ELM applying local historic training data, which establishes the building of a simple CA modelling approach that can be utilised without taking into account the complicated theory of traditional modelling approaches and several physical parameters. The integration of the ELM with the traditional forest fire CA framework proposes a new cellular automaton modelling approach. The performance was validated by applying information collected from five fires in the west of the United States. The produced results depict that the ELM performed sufficiently in predicting each cell's igniting probability. The impact of wind velocity on fire spreading patterns can be effectively defined by the proposed modelling approach. The validation against actual fire behaviour observations shows that its simulation performance is accurate and an improvement can be observed from previously reported studies.

An ANN tool was applied in [92] to simulate the rate of spread (ROS), flame height and flame angle in fires propagating in a bed of P. pinaster needles. Based on experimental data found in the literature, the optimum architecture of the ANN was trained and validated, in order to generalise the prediction of ROS, flame height and flame angle under different configurations not included in the database. The validation using a set of experimental data which are not handled to calibrate the proposed model depicted good performance of this ANN model for the prediction of the flame characteristics such as flame heigh and flame angle and rate of spread in fires propagating in a bed of P. pinaster needles. Furthermore, this model has been compared to three literature models; 2 physical models and 1 semi-empirical model and the results extracted are very comparable. All the models tested have been confronted with two other sets of experimental data from literature works. The ANN was applied to an application, where it proved powerful and effective in the evaluation of the ROS, flame height and flame angle by using information not included in the database.

Forest wildfires require high financial and social costs to measure, predict and control. One key challenge is modelling the dynamics of fire spread itself which usually relies on computationally expensive, handcrafted physics-based models. One of the essential problems is the creation of the dynamics model, treating wildfire as an agent spreading across a landscape in response to neighbourhood environmental and landscape parameters. The modelling problem in [93] can be depicted as a MDP where the fire is the agent at any cell in the landscape deciding whether to spread the fire into neighbouring cells. The set of suitable actions the fire can take at any point in time encompasses moving North, South, East, West or not spreading at all. Rewards are granted at the end of the epoch depending on the accurate classifying cells which are on fire or not. The authors used two algorithms for this problem, the Value Iteration and the Asynchronous Advantage Actor-Critic (A3C) which is a recent direct policy search approach that applies Deep Learning to perform simultaneous state-space approximation and policy representation. The information for the start state and rewards come solely from satellite images of a region in northern Alberta, Canada which is prone to large wildfires. Experiments occur training a wildfire spread policy for one region on multiple time frames as well as testing the transferability of that policy to the data from a second region. The results obtained indicate that it is helpful to rather a fire as a learning agent to comprehend its characteristics in a spatial environment. Previous work on the application of reinforcement learning to spatial processes has investigated modelling the state variable to represent the land cover and environmental characteristics and the action variable to represent the interaction between characteristics of the neighbourhood geographic space. The authors utilise these general principles in this work to wildfire prediction. This work is comparable to the applications of intelligent systems for predicting burned areas. However, the authors research the more specific problem of prediction of actual fire spread location over the short term. This study applies easily accessible satellite data from government agencies.

Wildland-human interfaces are comprised of WUIs, wildland-industrial interfaces (WIIs), and wildland infrastructure interfaces. WII can be defined as an area where oil & gas facilities or other industrial plants converge with or are located within wildland vegetation. Most previous works and attempts in modelling and risk assessment of wildfires in wildland-human interfaces have been devoted to wildlands or WUIs with very few studies on WIIs. Modelling and risk assessment of fires in WIIs is important because, in addition to the potential of damage to industrial facilities, the loss of revenue due to the facilities' operations shutdown but also to safety concerns or repair and replacement of damaged units could be considerable. Wildfires in WIIs can cause catastrophic consequences, particularly considering oil and gas facilities. Exposed to the heat of wildfire, storage tanks of flammable and explosive petroleum products such as crude oil, gasoline, diesel, kerosene, and propane can get damaged and aid the fire spread to more units and storage tanks. To assure the protection of oil and gas facilities from wildfires and the wildlands from potential ignitions at the facilities buffer zones are critical. To create the buffer zone some, form of vegetation-free ground, between the facilities and forest vegetation can be constructed. In the absence of specialised fire spread modelling and risk assessment methodologies in WIIs, such buffer zones are usually resolved by approximation analysis. However, these buffer zones are not sufficient in most cases. Khakzad in [94] developed a methodology by integrating dynamic Bayesian network (DBN) and FBP models to simulate the spread of wildfires in WIIs. Taking into account how influential parameter wind is in controlling the direction of fire spread, the Canadian FBP system was engaged to derive the fire's rate of spread and intensity, which in turn were to be applied to calculate the conditional fire spread probabilities among the nodes of the DBN. When the spread probabilities were known, the most probable path of fire and respective burn probabilities were identified by the DBN. In developing the model in [94], the authors made simplifying assumptions such as constant weather and fuel conditions, which in conjunction with the uncertainties embedded in the FBP system with regard to the prediction of fire's rate of spread and intensity, can cause a decrease in the accuracy of the burn probabilities. The model predictions should only be used as a guide to help land-use developers, firefighters, and plant owners get a better handle of the fire's most probable path and burn probabilities, and accordingly optimise their risk management strategies. In the absence of fire spread models in WIIs, the developed model, despite its limitations, is the first of its kind and can provide a new direction in modelling and risk assessment of wildfires in WIIs.

In [95], Palaiologlou et al. created and investigated a new approach that prototypes the utilisation of open-access data to develop datasets needed for wildfire simulations. The system was designed to acknowledge further applications in the Mediterranean region and the European regions. The authors used the system in Macedonia, Greece for testing, due to having one of the highest ignition densities in the country 76/ha and approximately 120,000 ha burned from 2000 to 2019. Various factors encompassing the extreme future climate, large continuous forested lands, and the large population of 2.5 million people, suggest that Macedonia is in danger of a large catastrophic fire to be observed. The authors utilised fire simulation modelling to assess community exposure and to map community 'firesheds' that characterise the area across all land ownerships which can likely transmit wildfire to communities. The authors also utilised the simulation outputs to map several landscape metrics that show the spatial scale of fire size and the complexity of wildfire exposure in relation to the geography of land tenures. The outcomes can have wide application to landscape fuel management policies in Greece.

The computational cost of predicting wildland fire spread across large, diverse landscapes is substantial using current models, which limits the ability to use simulations to develop mitigation strategies or perform forecasting. This paper [96], presents a ML approach to estimate the time-resolved spatial evolution of a wildland fire front using a deep convolutional inverse graphics network (DCIGN). The DCIGN was trained and tested for wildland fire spread across simple homogeneous landscapes as well as heterogeneous landscapes having complex terrain. Data sets for training, validation, and testing were created using computational models. The model for homogeneous landscapes was based on a rate of spread from the model of Rothermel, while heterogeneous spread was modeled using FARSITE. Over 10,000 model predictions were made to determine burn maps in 6 h increments up to 24 h after ignition. Overall, the predicted burn maps from the DCIGN-based approach agreed with simulation results, with mean precision, sensitivity, F-measure, and Chan–Vese similarity of 0.97, 0.92, 0.93, and 0.93, respectively. Noise in the input parameters was found to not significantly impact the DCIGN-based predictions. The computational cost of the method was found to be significantly better than the computational model for heterogeneous spatial conditions where a reduction in simulation time of 102105 was observed. In addition, the DCIGN-based approach was shown to be capable of predicting burn maps further in the future by recursively using previous predictions as inputs to the DCIGN. The ML DCIGN approach was able to provide fire spread predictions at a computational cost three orders of magnitude less than current models.

In [97], Radke et al. state the complexity of a single discipline to effectively mediate and predict wildfire growth is significant. Henceforth, FireCast was developed as a novel solution that combines AI and GIS to predict future wildfire spread, considering a small number of location characteristics and a weather forecast. AI techniques can make classifications or predictions about a given target based on a set of input features, and GIS can generate the appropriate geospatial input variables for such an AI model. FireCast applies supervised learning and geospatial inputs similarly to satellite imagery, elevation data, weather data, and historical fire perimeters to determine patterns correlated with fire spread in certain environments to produce predictions of wildfire spread. The historical fire perimeters were manually mapped by firefighters working to contain the fires. FireCast is the first application of supervised ML for wildfire spread prediction. While the training and the evaluation information is limited to the Rocky Mountain region of the United States, FireCast can scale to various regions with proper training data. The authors conducted experiments and evaluated the predictive power of FireCast both statistically and visually, and measured it against the most common predictive modelling software used by firefighters today. This study could aid to decrease the impact of wildfires, saving lives as well as major costs of infrastructure.

From the above research, it is shown that several models and tools can be widely applied for the goal of detection and response. The significant advances in wildfire monitoring and observation can be primarily traced to the increasing availability and capability of remote-sensing technologies. Several satellites (e.g., NASA TERRA and AQUA, NOAA GOES), for instance, have onboard fire detection sensors such as Advanced Very High-Resolution Radiometer, MODIS, and VIIRS. The aforementioned sensors, along with those on other satellites e.g., LANDSAT series, routinely monitor vegetation distributions and changes. Additionally, improvements in numerical weather prediction and climate models are simultaneously offering smaller spatial resolutions and longer lead forecast times, which potentially offers improved predictability of extreme fire weather events. Such developments make a data-centric approach to wildfire modelling a natural evolution for many research problems given sufficient data. The models studied depict great promise in the sufficient and fast detection of future wildfire events and the aid of making the response efforts faster, easier and safer.

Table 2 Summary of Detection and Response Models

Reference	Weather Data	Fire & Smoke Detection Method	Environmental Management	Fuel Consumption	Fire Spread Rate	Response Management	Method
Costafreda-Aumedes et al. [32]	National Wildland Fire Statistics Estadística General de Incendios Forestales (EGIF)	Not applicable	Not applicable	Not applicable	Not applicable	All-in-one emergency agencies or forest services, the ministry of Environment and Rural and Marine Affairs, Civil protection of the Ministry of Interior, and the Army Emergency Unit	ANNs
Rodrigues et al. [36]	Daily ERA-Interim gridded data at 12:00 am from the European Centre for Medium-Range Weather Forecasts	Not applicable	Not applicable	Not applicable	Not applicable	The Spanish EGIF database	Spatial modelling with RF
Julian and Kochenderfer [33]	Not applicable	Not applicable	Not applicable	Not applicable	Not applicable	Deep reinforcement learning (DRL) to guide the	A partially observable Markov decision process (POMDP), DRL.

						aircraft around a wildfire	
Arrue et al. [47]	information from meteorological sensors and from a geographical information database.	The FAR system is composed of a sensor interface, an image-processing tool, and a decision function	The Forest Fire Prevention and Restoration Service of the Regional Environment Agency in Andalucía	Information from topographic, fuel, and use maps	Not applicable	Not applicable	The FAR system consists of applying new IR-image processing techniques and ANNs
Sayad et al. [27]	Information was acquired from The Canadian Wild-land Fire Information System (CWFIS)	The MODIS LST products are archived in Hierarchical Data Format Earth Observing System (HDF-EOS) format files	The NDVI, which is a vegetation index that indicates the state of crop health, The Canadian Forest FWI System	The NDVI, which is a vegetation index that indicates the state of crop health	The CWFIS, The Canadian Forest Fire Behaviour Prediction (FBP) System	Not applicable	Neural Networks and SVM
Liu et al. [53]	Not applicable	A forest fire detection system that has an ANN algorithm implemented in a wireless sensor network (WSN).	The MODIS data products were retrieved from the online Data Pool, courtesy of the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and	Not applicable	Not applicable	Not applicable	Multi-criteria detection is implemented by the ANN algorithm.

			Science (EROS) Center				
Zhao et al. [54]	Not applicable	SVM Based Forest Fire Detection Using Static and Dynamic Features	Hubei Provincial Natural Science Foundation of China, National Basic Research Program of China	Not applicable	Not applicable	Not applicable	The dynamic SVM classification is performed on continuous video frames with the dynamic features
Barboutis et al. [49]	Not applicable	A novel image-based fire detection approach, which combines the power of modern deep learning networks with multidimensional texture analysis based on higher-order LDS.	European Environment Agency	Not applicable	Not applicable	Not applicable	Faster Regions with Convolutional Neural Networks (R-CNN) and spatial texture analysis (Grassmannian VLAD encoding)
Zhang et al. [48]	Not applicable	Faster R-CNN was used to detect smoke in forest.	Not applicable	Not applicable	Not applicable	Not applicable	Faster R-CNN was used to detect smoke in forest.
Li et al. [50]	Not applicable	3D parallel fully convolutional network (3D-PFCN) for	Not applicable	Not applicable	Not applicable	Not applicable	A pyramid classification and a parallel structure of 3D convolution and 3D pooling

		wildfire smoke detection					
Cao et al. [55]	Not applicable	Early forest fire smoke detection.	Not applicable	Not applicable	Not applicable	Not applicable	An attention enhanced bidirectional LSTM network (ABi-LSTM) for early forest smoke recognition.
Alexandrov et al. [52]	Not applicable	ML designed for the detection of wildfires using unmanned aerial vehicles (UAVs).	UAVs environmental monitoring	Not applicable	Not applicable	Not applicable	Classical methods of ML and deep learning methods such as Haar and LBP cascades, Faster R-CNN, Single Shot Detector (SSD), and YOLO (You Only Look Once).
Phan et al. [56]	Weather information	An autonomous and intelligent wildfire detection system.	Geostationary Operational Environmental Satellites (GOES-16) streaming data source.	Not applicable	Spatial dependency: consider the spatial context such as neighbouring pixels of a given pixel because wildfires spreads via	Not applicable	A novel wildfire detection method that utilises satellite images in an advanced deep learning architecture for locating wildfires at pixel level.

					near-by location.		
Ba et al. [57]	Not applicable	A new large-scale satellite imagery smoke detection benchmark based on MODIS data, namely USTC_SmokeRS	The Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center located in the Goddard Space Flight Center in Greenbelt, Maryland, USA	Not applicable	The model for the discrimination of smoke pixels and spreading areas in an image.	Not applicable	A new CNN-based method to detect the smoke scenes using satellite remote sensing.
Zhao et al. [51]	Not applicable	The saliency detection method is used to locate core fire area and extract fire regions into multiple fire images.	Envisat satellite image of wildfire	Not applicable	Not applicable	Not applicable	Saliency detection and deep convolutional neural network for localisation and recognition of wildfire in aerial images.
Linn et al. [59]	Meteorological Conditions present during the Oso complex fire.	Not applicable	Not applicable	Fuel conditions present during the Oso complex fire.	The fire spread rate will be calculate using BEHAVE	Not applicable	FIRETEC a combined with the hydrodynamics model HIGRAD in order to simulate wildfires using a terrain-following

							three-dimensional finite volume grid.
Riaño et al. [58]	Not applicable	Not applicable	Not applicable	Estimation of fuel moisture content using neural networks with the Leaf Optical Properties Experiment (LOPEX) database.	Not applicable	Not applicable	ANN were tested to estimate fuel moisture content
Pierce et al. [60]	Fire Family Plus to derive fire weather parameters	Not applicable	The climate is Mediterranean and is characterised by warm, dry summers and cold, wet winters.	Map four key canopy fuels variables: Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and canopy Height (HT) and used Landsat 5 spectral bands 1–5, and 7 as well as the NDVI and the Tasseled Cap Greenness, Brightness, and Wetness	The Monitoring Trends in Burn Severity (MTBS) dataset for the Bluff (2004) fire	Not applicable	RF to model and map forest canopy fuels for fire behaviour analysis in Lassen Volcanic National Park (LVNP), California, USA

Riley et al. [61]	Not applicable	Not applicable	Not applicable	The Landfire project provides over 20 national geo-spatial layers, including topographic, fuel, and vegetation layers, on 30m grids	Not applicable	Not applicable	A modified RF approach for imputing forest plots to a set of target landscape grids.
López-Serrano et al. [62]	Not applicable	Not applicable	The Sierra Madre Occidental, in the north of the state of Durango (Mexico), and covers an area of 1,142,916 ha	The United Nations Framework Convention on Climate Change (UNFCCC), which has identified AGB as an Essential Climate Variable	Not applicable	Not applicable	The k-Nearest Neighbours (k-NN), RF and SVM ML algorithms are being utilised for calculating aboveground forest biomass with remote sensing datasets
García et al. [63]	Not applicable	Light Detection and Ranging (LiDAR) data	The UK Natural Environment Research Council (Airborne Remote Sensing Facility 2006 Mediterranean Campaign, grant WM06-04)	Multispectral data to map fuel types has been demonstrated	Not applicable	Not applicable	A SVM classification combining LiDAR and multispectral data.
Amatulli, and Camia [64]	Meteorological data were	Not applicable	Changing climate in the EU-	A rating of fire danger through	Fire spread-ISI	Not applicable	MLR, RF, MARS

	extracted from the 40 Year Re-analysis Data Archive of the European Centre for Medium Range Weather Forecast		Mediterranean countries	fuel moisture			
Adab [65]	MODIS weather data	Fire monitoring was performed using data from the MODIS	MODIS	MODIS FMC data	Not applicable	Not applicable	Constructed landfire hazard maps by BLR and ANN methods
Bisquert et al. [66]	MODIS land surface temperature data	MODIS fire monitoring data	MODIS environmental data	MODIS FMC data	Not applicable	Not applicable	LR and ANN
Oliveira et al. [67]	Not applicable	Not applicable	Mediterranean area data	Not applicable	Corine Land Cover and point survey data	Not applicable	MLR and RF
Vasconcelos et al. [68]	Not applicable	Data on fire ignition locations are collected by several Forest Service field team	Not applicable	Not applicable	Arson data	Not applicable	LR and ANN
Vilar et al. [69]	Not applicable	Not applicable	Not applicable	Not applicable	The expansion of WUI due to urban development	Not applicable	ML Maximum Entropy models and GLM

Duane et al. [70]	Not applicable	Not applicable	Mediterranean landscapes	Not applicable	Not applicable	Not applicable	ML Maximum Entropy
Yago et al. [72]	MODIS FWI data	Not applicable	Mediterranean region	MODIS fuel data	Not applicable	Not applicable	Maximum Entropy algorithm
Vacchiano et al. [73]	Mean annual temperature	Not applicable	Osta Valley region in northwest Italy	Not applicable	Education and prevention of negligence during the winter time	Not applicable	Maximum Entropy algorithm
Markuzon and Kolitz [85]	Landsat land cover data and National Oceanic and Atmospheric Administration (NOAA) weather observations	Fire monitoring was performed using data from the MODIS	Land cover information collected by Landsat Thematic Mapper satellite.	Publicly available data as a proxy for data on combustible material, namely land cover information collected by Landsat Thematic Mapper satellite	Not applicable	Not applicable	Data mining methods to develop fire prediction models. RF, DT, BNs and k-NN.
Artés et al. [86]	Not applicable	Not applicable	Not applicable	Dead fuel moisture, live fuels moisture	Wind speed, and wind direction among others to undertake forest fire spread forecasting in real time	Not applicable	FARSITE simulation engine with a Time-Aware Classification

Houssami et al. [87]	Not applicable	Not applicable	Not applicable	Experiments were conducted by burning beds of pine needles and WUI	A multiphase formulation that allows the fire rate of spread	Not applicable	Sub models used to close CFD models particularly with the multiphase approach for wildfires.
Denham et al [88]	Not applicable	Not applicable	Global environmental change conditions	Vegetation fuel type	Analysis of fire spread based on maps of burnt areas without knowing the point of origin of the fires or how they spread	Not applicable	GA
Ascoli et al. [89]	Days since last rain, air temperature and humidity, and wind speed	Not applicable	The complete dataset of ROS observations and environmental conditions during fire experiments is available on Comprehensive R Archive Network2 as example data (firexp) in the Rothermel package for R	Fuel models for litter, grass and shrub fuels	The Rothermel fire spread model.	Not applicable	GA in the Rothermel fire spread model.

Kozik et al. [90]	Not applicable	Not applicable	Geoinformation system such as Google Maps	The parameters of the ambient medium, such as the forest type, humidity, amount of the combustible material, and depth of the layer of the combustible material	The wind velocity and direction, calculation of the wind chart on the basis of the information about the relief and visualisation of fire evolution	Not applicable	Adaptive Prediction of Forest Fire Evolution on the Basis of Recurrent Neural Networks
Zheng et al. [91]	The RAWS USA Climate Archive	The fire's driving force data were collected from the LANDFIRE	Not applicable	Existing vegetation data (i.e., Existing Vegetation Type, Existing Vegetation Cover, and Existing Vegetation Height) were downloaded from the 2001 version product of the LANDFIRE program	Forest fire spread simulating model	Not applicable	Forest fire spread simulating model using cellular automaton with extreme learning machine
Chetehouna et al. [92]	Not applicable	Not applicable	Not applicable	FMC and a P. pinaster fuel bed	The model predicts the flame height, flame angle	Not applicable	ANN

					and rate of ROS of a bed of P. pinaster needles.		
Subramanian and Crowley [93]	Temperature is obtained from processing thermal images from satellites	Not applicable	The USGS Earth Explorer data portal	Not applicable	The Bellman Equation	Not applicable	MDP, Asynchronous Advantage Actor Critic and RL to augment physics-based forest wildfire simulations
Khakzad [90]	Weather conditions such as temperature, relative humidity, and wind speed	Not applicable	WUIs and WIIs	Parameters such as burning index, fire potential index, drought index, thousand-hour fuel moisture	A BN for modelling the spread of fire	Not applicable	DBN and FBP models to simulate the spread of wildfires in WIIs.
Palaiologou et al. [95]	GIS weather data	Not applicable	GIS topological data	GIS fuel data	Monte Carlo fire simulations with the Minimum Travel Time fire spread algorithm	Not applicable	Minimum Travel Time fire spread algorithm.
Hodges et al. [96]	Not applicable	Not applicable	Not applicable	Rothermel fuel model	Rothermel and FARSITE	Not applicable	Wildland-Urban Interface Fire Dynamics

							Simulator using DCIGN
Radke et al. [97]	GIS weather data	Not applicable	GIS topological data	GIS fuels data	The FARSITE model	Not applicable	FireCast, a novel solution that combines AI and GIS

RESTORATION AND ADAPTATION MODELS

The post-fire condition of a burned landscape directly relates to the type and condition of the forest and the severity of the burn. Fire ecologists use the term burn severity to refer to the effects of fire on soil conditions and hydrologic function. In general, the denser the pre-fire vegetation and the longer the fire burns on a particular site, the more severe the effects on soil and its ability to absorb and process water.

Intense, severe wildfires may destroy almost everything in a forest, from the tall trees and small bushes to the grass on the ground and even the dead leaves and roots. Thus, when a high-severity wildfire occurs, it removes all these protective elements from the forest floor. A severe wildfire may also cause certain types of soil to become hydrophobic by forming a waxy, water-repellent layer that keeps water from penetrating the soil and dramatically amplifying the rate of runoff. The loss of critical surface vegetation leaves forested slopes extremely vulnerable to large-scale soil erosion and flooding during subsequent storm events. These risks, in turn, threaten the health, safety and integrity of communities and natural resources that are downstream.

Consequently, in this subsection, the restoration and adaptation models are investigated. As illustrated in Figure 5 Sub-categories of Restoration and Adaptation , the various models are organised based on three main sub-categories: (a) Soil Erosion and Deposits, (b) Smoke Particulate Levels and (c) Fire Perimeter and Severity Mapping. Moreover, Table 3 summaries these models in terms of weather data, environmental factors, fire data, restoration and adaptation techniques, socio-economic factors and methods.

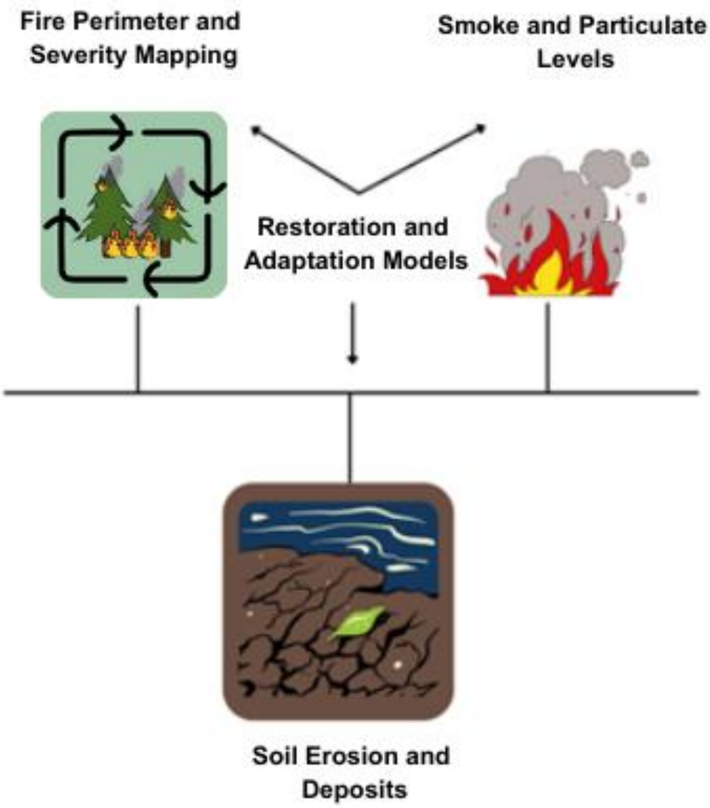

Figure 5 Sub-categories of Restoration and Adaptation Models

SOIL EROSION AND DEPOSITS

Mallinis et al. [98] modelled potential post-fire soil erosion risk following a large intensive wildfire in the Mediterranean area using CART and KM algorithms. In that paper, before the wildfire, 55% of the study area was classified as having severe or heavy erosion potential compared with 90% after the fire, with an overall classification accuracy of 86%. Meanwhile, Buckland et al. [99] applied ANNs to examine the relationships between sand deposition in semiarid grasslands and wildfire occurrence, land use, and climatic conditions. The authors made predictions of the future soil erosion levels considering climate change assumptions.

Forest fires in the Mediterranean region are a serious threat to the natural and anthropogenic environment. Post-fire soil loss leads to land degradation and desertification of the affected areas. Furthermore, observed expansion of WUI is likely to lead to more intense impacts on human resources and infrastructures. Therefore, robust, easy-to-implement procedures are needed to replace labour-intensive and time-consuming ones to predict soil loss–related hazards and assist in the prioritisation of mitigation measures. Under this perspective, the authors in [98] followed an approach for analytical risk assessment to estimate mitigation urgency at local and regional scales following major fire events. Post-fire severity and pre-fire land cover were defined utilising medium-resolution satellite images. The multi-temporal soil erosion risk is modelled within a GIS framework. EPM, a semi-quantitative model applied for the annual prediction of sediment yield and erosion severity estimation at the watershed scale by using spatial data of geology, soil, and land cover/use within a GIS environment. In addition, various landscape metrics were used to estimate the spatial configuration of the erosion process, a parameter not presently considered in post-fire soil erosion risk estimations. The proposed methodology is easily transferable across space and scale, while the difficulty of the approach is that verification of the results is not supported by extensive field measurements but by visual assessment.

Land degradation and sediment remobilisation in dryland environments can be a significant global environmental problem. Given the potential for currently stabilised dune systems to reactivate under climate change and enhanced anthropogenic pressures, detecting the role of external disturbances in driving geomorphic response is vitally important. The authors in [99] created a novel method, applying ANNs for time series of historical reactivation-deposition events from the Nebraska Sandhills, to determine the relationship between historic periods of sand deposition in semi-arid grasslands and external climatic conditions, land use pressures and wildfire occurrence. It was demonstrated that both vegetation growth and sediment re-deposition episodes can be evaluated. Sensitivity testing of individual factors demonstrates that localised forcings have a statistically significant impact when the climate is held at present-day conditions. However, the dominant effect is climate-induced drought. The proposed approach has great potential for evaluating future landscape sensitivity to climate and land use scenarios across a wide range of potentially fragile environments.

SMOKE AND PARTICULATE LEVELS

Smoke emitted from wildfires can lower air quality with adverse effects on the health of both humans and animals, as well as other impacts. Therefore, several ML methods have been utilised to comprehend the dynamics of smoke from wildland fire. For example, Yao et al. [97] used RF to predict the minimum height of forest fire smoke using data from the CALIPSO satellite. More commonly, ML methods have also been used to estimate population exposure to fine particulate matter, which can be useful for epidemiological studies and for informing public health actions. One such study by Yao et al. [96] also used RF to estimate hourly concentrations of PM2.5 in British Columbia, Canada. Zou et al. [98] compared RF, BRT, and MLR to estimate regional PM2.5 concentrations in the Pacific Northwest and found that RF performed much better than the other algorithms. Reid et al. [99] estimated spatial distributions of PM2.5 concentrations during the 2008 northern California wildfires. The authors of the aforementioned study utilised 29 predictor variables and compared 11 different statistical models, including RF, BRT, SVM, and KNN. Overall, the BRT and RF models showed the best performance. Emissions other than particulate matter have also been modelled, as [100] applied an ANN to predict carbon monoxide concentrations emitted from a peat fire in Siberia, Russia. In another study, the authors applied 10 different statistical and ML methods and 21 covariates (including weather, geography, land use, and atmospheric chemistry) to predict ozone exposures before and after wildfire events (Watson et al. [101]). Here, gradient boosting gave the best results with respect to both roots mean square error and R2 values, followed by RF and SVM. In another application related to smoke, Fuentes et al. [102] applied ANNs to detect smoke in several different grape varietals used for winemaking.

Exposure to wildfire smoke over 24-hour periods can be correlated with a wide range of acute cardiopulmonary events, but little is known about the effects of sub-daily exposures preceding these types of events. One challenge in researching sub-daily effects is the lack of spatially and temporally resolved estimates of smoke exposures. Inexpensive and globally applicable tools to reliably estimate exposure are required. The authors in [100] demonstrate a RF ML approach to calculate 1-hour average population exposure to fine particulate matter during wildfire seasons from 2010 to 2015 in British Columbia, Canada, at a 5km-by-5km resolution. The model uses remotely sensed fire activity, meteorology assimilated from various information sources, and geographical data. Compared with observations, model predictions correlated at 0.93, with a 3.2 µg/m3 root mean squared error, the mean fractional bias at 15.1%, and the mean fractional error at 44.7%. Spatial cross-validation demonstrated an overall correlation of 0.60, with an interquartile range from 0.48 to 0.70 across monitors. The proposed model can be applied for global use, even in locations without air quality monitoring. It can be valuable for epidemiologic studies on sub-daily exposure to wildfire smoke, and for informing public health actions if operationalised in near-real-time.

Forest fire smoke is a major public health concern as more intense and frequent fires are to occur due to climate change. Remote sensing can be a valuable tool for exposure assessment, but its applicability for health studies is limited because most products measures pollutants in the total column of the atmosphere, and not the surface concentrations most applicable to population health. Information about the vertical distribution of smoke is critical for addressing this limitation. The CALIPSO satellite can generate such data but it cannot cover all smoke events due to its narrow ground track.

The authors in [101] created a RF model to predict the minimum height of the smoke layer detected by CALIPSO at the high temporal and spatial resolution, applying data about fire activity in the geographic location and the meteorological conditions. These pieces of data are available in near-real-time, establishing that the resulting model can be easily operationalised. A total of 15,617 CALIPSO data blocks were detected as impacted by smoke within the province of British Columbia, Canada from 2006 to 2015, and 52.1% had smoked within the vicinity, where the population might be exposed. The final model interpreted 82.1% of the variance in the observations with a root mean squared error of 560 m. The most critical variables in the model were wind patterns, the month of smoke observation, and fire intensity within 500 km. Predictions from this model can be 1) directly utilised to smoke detection from the existing remote sensing products to generate another dimension of data; 2) incorporated into statistical smoke models with inputs from remote sensing products, or 3) applied to inform estimates of vertical dispersion in deterministic smoke models. These potential applications are expected to enhance the assessment of ground-level population exposure to forest fire smoke.

Large wildfires are a significant threat to the western U.S. In the 2017 fire season, extensive wildfires transpired across the Pacific Northwest (PNW). To estimate the public health impacts of wildfire smoke, numerical simulations and observations were combined in [102] for regional fire events during August-September of 2017. A one-way coupled Weather Research and Forecasting and Community Multiscale Air Quality modelling system were applied to simulate fire smoke transport and dispersion. To decrease modelling bias in fine particulate matter (PM2.5) and to optimise smoke exposure estimates, modelling results were integrated with the high-resolution Multi-Angle Implementation of Atmospheric Correction satellite aerosol optical depth and the U.S. EPA AirNow ground-level monitoring PM2.5 concentrations. Three ML-based data fusion algorithms were used: An ordinary multi-linear regression method, a generalised boosting method, and a RF method. 10-Fold cross-validation found enhanced surface PM2.5 estimation after data integration and bias correction, especially with the RF method. Lastly, to evaluate the transient health effects of fire smoke, the optimised high-resolution PM2.5 exposure was utilised to estimate a short-term exposure-response function. Total regional mortality attributable to PM2.5 exposure during the smoke episode was estimated at 183 (95% confidence interval: 0, 432), with 85% of the PM2.5 pollution and 95% of the consequent multiple-cause mortality contributed by fire emissions. This application shows both the profound health impacts of fire smoke over the PNW and the need for a high-performance fire smoke forecasting and reanalysis system to reduce public health risks of smoke hazards in fire-prone regions.

Calculating population exposure to particulate matter during wildfires can be arduous due to the insufficient monitoring data to capture the spatiotemporal variability of smoke plumes. Therefore in [103] chemical transport models (CTMs) and satellite retrievals generate spatiotemporal data that can aid in predicting PM2.5 during wildfires. PM2.5 concentrations during the 2008 northern California wildfires were estimated by applying 10-fold cross-validation (CV) to select an optimal prediction model from a set of 11 statistical algorithms and 29 predictor variables. The variables incorporate the CTM output, three measures of satellite aerosol optical depth, distance to the nearest fires, meteorological data, land use, traffic, spatial location, and temporal characteristics. The lowest CV root mean squared error was obtained by the generalised boosting model (GBM) with 29 predictor variables and had a CV-R2 of 0.803. The GOES Aerosol/Smoke Product (GASP) Aerosol Optical Depth (AOD) was the most critical, followed by the CTM output and distance to the nearest fire cluster. Parsimonious models with various combinations of fewer variables also predicted PM2.5 accurately. Applying ML algorithms to incorporate spatiotemporal data from satellites and CTMs to reliably predict PM2.5 concentrations during major wildfire events.

In [104] the authors presented a novel differential neural network model evaluating the dispersion of carbon monoxide (CO) emissions from a peat fire near a highway. The authors have developed methods for the optimisation of the model on the basis of simulated and experimental measurements of CO concentrations in the area of dispersion of the smoke cloud. The numerical solutions of the problem have been presented in the form of neural network approximations by the Gaussian model and in the form of neural network approximate solutions of partial differential equations. The trained neural network model can be applied for the prediction of an emergency when wind speed and direction and other fire parameters are changing. The results of the study depict that the methods created can be recommended as a useful tool for air quality management and forecasting as well as for the prediction and prevention of such emergencies.

Epidemiologists apply prediction models to downscale (i.e., interpolate) air pollution exposure where monitoring data is insufficient. The authors in [105] compare ML prediction models for ground-level ozone during wildfires, evaluating the predictive accuracy of ten algorithms on the daily 8-hour maximum average ozone during a 2008 wildfire event in northern California. Models were assessed using a leave-one-location-out cross-validation (LOLO CV) procedure for accounting for the spatial and temporal dependence of the data and producing more realistic estimates of prediction error. LOLO CV avoids both the well-known overly optimistic bias of k-fold cross-validation on dependent data and the conservative bias of evaluating prediction error over a coarser spatial resolution via leave-k-locations-out CV. Gradient boosting had the highest accuracy of the ten ML algorithms with the lowest LOLO CV estimated root mean square error (0.228) and the highest LOLO CV (0.677). RF was the second-best performing algorithm with a LOLO CV of 0.661. The LOLO CV estimates of predictive accuracy were less optimistic than the 10-fold CV estimates for all ten models. The difference in predicted accuracy between the 10-fold CV and LOLO CV was greater for more flexible models like gradient boosting and RF. The order of predicted model accuracy was affected by the choice of evaluation metric, indicating that 10-fold CV and LOLO CV may select different models or sets of covariates as optimal, which calls into question the reliability of 10-fold CV for model selection. These prediction models are created for interpolating ozone exposure and are not suited to inferring the effect of wildfires on ozone or extrapolating to predict ozone in other spatial or temporal domains. This is shown by the inability of the best-performing models to accurately predict ozone during the 2007 southern California wildfires.

Bushfires are more frequent and intensive due to the changing climate. Those that transpire close to vineyards can provoke smoke contamination of grapevines and grapes, which can influence wines, producing smoke taint. At present, there are no available practical in-field tools available for the detection of smoke contamination or taint in berries. Therefore, the authors in [106] propose a non-invasive/in-field detection system for smoke contamination in grapevine canopies founded on predictable changes in stomatal conductance patterns based on infrared thermal image analysis and ML modelling based on pattern recognition. A second model was also created to quantify levels of smoke-taint-related compounds as targets in berries and wines using near-infrared spectroscopy (NIR) as inputs for ML fitting modelling. The results depict that the pattern recognition model to detect smoke contamination from canopies had 96% accuracy. The second model to predict smoke taint--- compounds in berries and wine fit the NIR data with a correlation coefficient (R) of 0.97 and with no indication of overfitting. These methods allow grape growers to utilise quick, affordable, accurate, and non-destructive in-field screening tools to assist in vineyard management practices to minimise smoke taint in wines with in-field applications using smartphones and unmanned aerial systems (UAS).

The section has discussed the restoration of biospheres and ecosystems post-wildfire instances, as well as the adaptation to new parameters, predominately introduced by the advent of climate change. It was analysed how the conditions of an affected landscape in a post-fire scenario are correlated to the local fuel typology, the condition of the flora and the overall estimate for the severity of the burn. It is deducted that as a general rule, the severity of the wildfire's effects on soil and its water-absorbing and processing capacity is directly proportional to the density of the pre-fire vegetation, as well as the duration of the fire burn. As a long-term effect, serious burns of a wildfire may result in some soil types becoming near-hydrophobic, as a new layer of burned material is introduced to the soil. This has a cascading and amplifying effect, as the rate of runoff is severely increased, effectively rendering the area more prone to violent soil erosion after storms and severe rainfall. All aforementioned risks, seriously threaten the well-being of affected communities and the availability of natural resources. To conclude, this subsection constitutes an attempt at documenting the aforementioned issues while investigating the restoration and adaptation potential of several models and methods, directly associated with climate change, soil erosion, and smoke particulate levels restoration and finally adaptation models.

FIRE PERIMETER AND SEVERITY MAPPING

This section will focus on maps of the final burn perimeter and fire severity, which hold significance in evaluating and forecasting the economic and ecological consequences of wildland fires, as well as in recovery planning. Historically, fire perimeters were sketch-mapped from the air, from the ground or aerial GPS or other traverses. Creating methods for mapping fire perimeters and burn severity from remote sensing imagery has been an area of active research since the advent of remote sensing in the 1970s and is concerned with classifying active fire areas.

In early studies [107] using ML methods for fire mapping, ANNs were used for burn-scar mapping. Pu and Gong in [108] compared logistic regression (LR) with ANN for burn-scar mapping using Landsat images, both methods achieved high accuracy (>97%). Interestingly, however, the authors found that LR was more efficient for their relatively limited dataset. Dragozi et al. [109] compared the utilisation of SVM against a nearest neighbour method for burned-area mapping in Greece and found better performance with SVM. In fact, a number of studies ([55], [110]) have successfully used SVM for burn scar mapping using satellite data.

In [110] the authors used a one-class SVM, which requires only positive training data (i.e., burned pixels), for burn-scar mapping, which may offer a more sample-efficient approach than general SVMs, the one-class SVM approach it can be valuable when good wildfire training datasets are hard to find. One recent paper used a five-layer DNN for mapping fires in Interior Alaska with a number of MODIS-derived variables (e.g., NDVI and surface reflectance). They found that a validation-loss weight selection strategy for the unbalanced dataset allowed them to achieve better accuracy compared with an XGBoost method; however, without the validation-loss approach, XGBoost outperformed the DNN, highlighting the need for methods to deal with unbalanced datasets in fire mapping.

The FIREMON: Fire effects monitoring and inventory system was created in [111]. In order to effectively document wildfire effects and to assess the damage dealt to the overall ecosystem, and the short- and long-term impacts it yields on an area, it is of utmost importance to effectively and pre-emptively monitor and assess the risk, whilst also evaluating the success or failure of a burn. Additionally, responsible stakeholders are expected to appraise and validate the potential for future treatments and wildfire mitigation measures as a whole. Nevertheless, monitoring wildfire effects is often challenging, as data collection is a demanding task, requiring substantial funds, as well as resources and sampling expertise, the latter being a key bottleneck when implementing wildfire monitoring in many cases: relevant agencies and stakeholders lack the standardised protocols to satisfy their distinct objectives. In light of the above-mentioned remarks, C. D. Lutes et al. propose and develop a comprehensive system, called "Fire Effects Monitoring and Inventory System" (FIREMON). The proposed platform is engineered to satisfy the requirements of fire management agencies in terms of monitoring and inventory for a spectrum of ecosystems, fuel typologies and geography (mainly focused on the United States). The platform is comprised of standardised sampling techniques, databases, field forms, data analysis frameworks, as well as an image analysis guide so that stakeholders are able to effectively monitor wildfire effects, collect and store all sampled data, extract valuable insight from the data and summarise it while also linking it with satellite imagery, and lastly, the map said sampled data across the target geography using image processing in a modular fashion.

In [107], K. R. Al-Rawi et al. engage in a thorough analysis pivoted towards studying a multitude of wildfire phenomena in Valencia, Spain. Monitoring of fire occurrence was implemented by means of visualising smoke propagation and mapping the area affected by the wildfire. The study took place throughout the entirety of the fire period of 1994. The researchers monitor the spatio-temporal evolution of the wildfires under investigation on a daily basis. It is concluded that the approach using burned area mapping performs measurably better in comparison to other monitoring approaches, due to the fact that burned area mapping can detect the individual pixels that burn between two consecutive images. Moreover, the authors considered an approach which revolved around considering the pixels beneath the flames as aflame themselves, which will overestimate the size of the fire. The considered approaches were benchmarked and documented. As a concluding remark, a fire manifesting itself in several instances should be watched carefully due to the exponential increase of the wildfire propagation rate, after each consecutive instance of the fire. It is deduced that, although the burned area mapping approach is well-sufficient for defining and monitoring the fire propagation map as well as the recently affected area.

Based on the experimental results in [108], it can be demonstrated that (1) from the viewpoint of efficiency the LR method performs better than the neural network (NN) algorithm method, but both techniques produce similar and acceptable results (overall average accuracy greater than 97% for both methods at the two study sites) when they are applied to evaluate probabilities of burned scars from a single post-fire Landsat 7 ETM (2) among all six original TM bands and five vegetation indices, the original TM4 and TM7, NDVI1 (TM4, TM7), and NDVI2 (TM4, TM3) have the greatest discrimination power in distributing the burned and unburned areas; (3) the predictive accuracy generated with samples from the shaded and shadowed areas is lower than from sunlit areas; and (4) based on the performance of the LR and NN in predicting burned scars with datasets extracted from a single post-fire Landsat 7 ETM image at the two study sites, the LR and NN techniques can be employed in other areas similar to the study sites. However, if ideal datasets are available, some more traditional methods (such as LDA) should be considered before using the more powerful methods (e.g., LR and NN).

In [112], the authors aim to address the problem of burnt area mapping from remote sensing images. Here, the assessment of the burnt land discrimination is only founded on a single after-fire satellite image acquired by the SPOT5 satellite. To delineate burnt areas, the classification method called SVM was utilised. This proposed method is compared with other traditional classifiers like the K-Nearest Neighbours or the K-Means algorithms which are widely applied in pattern recognition as reference classification methods. The results provided by the different classifiers are also compared with official burnt area statistics, procured from ground truths.

In [109], the authors aim to address the problem of burned area mapping by applying a single post-fire Very High Resolution (VHR) satellite image. In this study, the efficiency of the two classifiers SVM and k-NN were examined in classifying image objects for accurate mapping of recently burned areas. The general conclusion drawn from this study was that both classification models generated very accurate burned area maps. Although, the results demonstrate that the SVM classifier achieved higher accuracy in the overall classification compared to the NN, despite the fact that the statistical differences are very small. Also, it should be noted that SVM showed a better ability in differentiating the different classes. In conclusion, presently the main drawback of this object-oriented SVM method is that it is difficult to be utilised as an operational tool for burned area mapping, as in most cases the present SVM-based method cannot be applied in a single software interface.

In [110], the authors applied the VIIRS in active fire data (375 m spatial resolution) to automatically extract multispectral samples and train a One-Class SVM for burned area mapping and used the resulting classification algorithm to 300-m spatial resolution imagery from the Project for On-Board Autonomy-Vegetation (PROBA-V). The active fire data were screened to prevent the extraction of unrepresentative burned area samples and combined with surface reflectance bi-weekly composites to produce burned area maps. The procedure was used over the Brazilian Cerrado savanna, examined with reference maps obtained from Landsat images and compared with the Collection 6 MODIS Burned Area product (MCD64A1). The evaluation demonstrates that the algorithm generated enhanced the detection of small-sized scars and showed results more similar to the reference data than MCD64A1. Unlike active fire-based region growing algorithms, the proposed method allows for the detection and mapping of burn scars without active fires, thus eliminating a potential source of omission error.

Several techniques can be employed to generate precise and reliable fire severity maps from satellite imagery, a crucial aspect for documenting fire regimes and establishing priorities for post-fire management. Notably, machine learning methods have demonstrated significant potential in mapping wildfire severity within woodland and forest ecosystems through the analysis of satellite imagery.

The study by Collins et al. [113] delves into the classification of fire severity in the diverse ecosystems of southern Australia, encompassing forests, woodlands, and shrublands. Specifically, the authors employ a method cantered on random forest classification and Landsat imagery for automated mapping of fire severity. Their dataset, drawn from 33 wildfires and 57 prescribed burns occurring between 2006 and 2019, provides a robust foundation for model training and validation. The research classifies fire severity into five classes: a) canopy burnt, b) high canopy scorch, c) medium canopy scorch, d) low canopy scorch, and e) unburnt. Notably, the random forest classifier achieves an overall accuracy of approximately 88% for wildfires and 68% for prescribed burns across the studied fires. The observed disparity in accuracy between wildfires and burns is attributed to the lower performance in classifying low fire severity, which predominantly characterizes prescribed burns.

The study in [114] employed an RF classifier to enhance the precision of wildfire severity mapping across diverse landscapes utilizing Landsat imagery. The research utilized fire severity training data from sixteen significant wildfires in south-eastern Australia spanning the period from 2006 to 2016. Notably, the authors concentrated on high-resolution visible and infrared aerial photography captured shortly after the fire ignition date, coupled with Landsat imagery to generate pre- and post-fire cloud-free mosaics. The findings demonstrated the superior performance of RF classification compared to the differenced Normalized Burn Ratio (ΔNBR) classification across all severity classes. RF achieved an exceptional classification accuracy of over 95% for unburnt, crown scorch, and crown consumption severity classes, and a high accuracy of over 74% for low severity classes like crown unburnt and partial crown scorch. The research leveraged satellite-derived pre- and post-fire differenced severity indices, with Normalized Burn Ratio (NBR), NDVI, and Normalized Difference Water Index (NDWI) emerging as the most important spectral indices in the RF model. Furthermore, Google Earth Engine facilitated image acquisition, processing, and the production of severity maps.

In [115], the authors assess various methodologies for classifying and mapping fire severity using multi-temporal Landsat Thematic Mapper data. The evaluation encompassed six approaches: two relying on temporal image differencing and ratioing between pre-fire and post-fire images, two employing principal component analysis of pre- and post-fire imagery, and two utilizing artificial neural networks. One artificial neural network approach used only postfire imagery, while the other incorporated both pre- and post-fire imagery. Reference data were derived through manual interpretation of vertical aerial photographs. Landsat imagery was selected for this study due to the strong correlation between the mid-infrared reflectance of vegetation and crucial vegetation canopy characteristics in relation to fire effects. The results exhibited variability within the burned and unburned categories across methods. Normalized Difference methods (ND) displayed lower sensitivity to burns, while ML methods excelled in classifying more lethal tree and shrub categories. Principal Components methods, on the other hand, demonstrated proficiency in classifying mixed tree and grass types. Beyond discrepancies in totals, class proportions, and sensitivity, distinct pattern variations emerged. ML methods generated a more homogeneous and blocky pattern, contrasting with the pixel classifications of Principal Components and Normalized Difference methods, which were neither filtered nor merged. The study focused on the Fort Howes wildfire complex in southeastern Montana, encompassing diverse forest, shrubland, and grassland vegetation types. The Normalized Burn Ratio emerged as a flexible, robust, and analytically simple approach. The single-date Machine Learning method proved to be the sole viable option when pre-fire image data are unavailable. The two-date Machine Learning method offered enhanced consistency with local or regional vegetation maps, leveraging both pre-fire and post-fire reference data.

Table 3 Summary of Restoration and Adaptation Models

Reference	Weather Data	Environmental Factors	Fire Data	Socio-Economic Factors	Method
Amatulli et al. [3]	Meteorological data were extracted from the 40 Year Re-analysis (ERA-40) Data Archive of the European Centre for Medium Range Weather Forecast (ECMWF)	The Regional Climate Model (RCM) HIRHAM,	Fire data were extracted from the European Fire Database of EFFIS.	NUTS3 level in Portugal	MLR, RF, MARS
Parks et al. [4]	climate data from numerous global climate models for the western US	Not applicable	fire frequency and area burned	Not applicable	A statistical model of fire severity as a function of climate, BRT
Yao et al. [100]	Hourly meteorological information was retrieved from the NASA Modern Era Retrospective-analysis for Research and Applications (MERRA) program	1-hour average PM2.5 measurements from 72 air quality monitoring stations from the Provincial Air Data Archive Website maintained by the British Columbia Ministry of Environment and Climate Change Strategy	Data from the MODIS instruments aboard the 155 polar orbit Aqua and Terra satellites	Human populations smoke exposal.	An RF model to estimate 1-hour average population exposure to fine particulate matter
Yao et al. [101]	Not applicable	The GTOPO30 product developed by the US Geological Survey EROS Center	The Fire Information for Resource Management	Human populations smoke exposal.	An RF model to predict the minimum height of the smoke layer observed by CALIPSO at high

			System (FIRMS) by NASA		temporal and spatial resolution
Zou et al. [102]	The Weather Research and Forecasting (WRF) model version 3.7 and the Community Multiscale Air Quality (CMAQ) model version 5.2	The U.S. EPA AirNow ground-level monitoring PM2.5 concentrations.	The Sparse Matrix Operator Kernel Emissions (SMOKE) model in the CMAQ system	Demographic data were collected from the 2010 USA Census Grids provided by the NASA Socioeconomic Data and Applications Center (SEDAC), Wide-ranging ONline Data for Epidemiologic Research (WONDER) of Centers for Disease Control and Prevention (CDC).	MAIAC: Multi-Angle Implementation of Atmospheric Correction. AOD: aerosol optical depth. MODIS, CMAQ: Community Multiscale Air Quality model. RF, GBM: Generalised boosting model.
Reid et al. [103]	The NCAR provided PM2.5 concentration estimates from the Weather Research and Forecasting with Chemistry (WRF-Chem) 3.2 model.	The California Air Resources Board (CARB), and the AirNow and AirFire databases	The 2008 northern California wildfires, MODIS Fire Detection points from the Remote Sensing Applications Center of the US Forest Service	Estimating human exposures that may vary on small spatial scales during wildfires.	Generalised linear models (GLM), RF, bagged trees, generalised boosting models (GBM), GAM, multivariate adaptive regression splines, elastic nets, SVMs with a radial basis kernel, Gaussian processes with a radial basis kernel, k-NN regression, and lasso regression.
Lozhkin et al. [104]	Not applicable	Not applicable	Peat fire characteristics	Dispersion of CO emissions from a peat fire near a highway.	The neural network model of the complex system can gather pieces of heterogeneous information – differential

					equations, conservation laws, equations of state, symmetry conditions, etc.
Watson et al. [105]	Weather Research and Forecasting with Chemistry (WRF-Chem)	The United States EPA	The Fire Inventory from NCAR (FINN) v1.5	Not applicable	elastic net regression, generalised additive models (GAM), gradient boosting, k-NN regression, lasso regression, linear models, MARS, neural network, RF, and SVMs with a radial basis kernel.
Fuentes et al. [106]	Micrometeorological weather data such as temperature, relative humidity, and solar radiation	Not applicable	Not applicable	Property damage after fire in vineyards	ML modelling techniques to assist growers confronted with vineyard exposure to smoke from bushfires, an issue which has been exacerbated in prominent wine regions around the world due to climate change
Young et al. [5]	Monthly mean temperature and total precipitation data from the climate research unit from 1950 to 2009	The Alaska, the boreal forest, and the tundra	30 (non-continuous) years of paired fire data	Not applicable	BRT
Moritz et al. [6]	Global climate model output from the World Climate Research Programme's Coupled Model Intercomparison Project	Spatial patterns in resources to burn and atmospheric conditions conducive to fire activity	The fire dataset used in this study spans from 1996-2007	Not applicable	MaxEnt models

	phase 3 multi-model dataset, average temperature and precipitation over a period of 1971–2000				
Mallinis et al. [98]	GIS weather data	GIS environmental data	GIS fire data	Not applicable	CART and KM
Buckland et al. [99]	The Niobrara Valley Preserve provided an integrated record of precipitation and temperature change over the past 400 years	Not applicable	Wildfire occurrence data	ANN defines the relationship between climatic and human disturbance forces	ANNs
Collins et al. [113]	Not applicable	environmental variation (e.g. climate, vegetation, terrain)	High resolution post-fire near-infrared aerial imagery data	Not applicable	RF
Collins et al. [114]	Not applicable	Not applicable	high resolution visible and infrared aerial photography and Landsat imagery from sixteen large wildfires that occurred between 2006 and 2016 in Victoria, Australia	Not applicable	RF
Brewer et al. [115]	Not applicable	Not applicable	image data temporal requirements	Not applicable	ANNs, PCA, ND

TREEADS WILDFIRE MODELS AND SERVICES

As part of the current deliverable, a first description of the wildfire models within the project is provided. A small Description of the proposed wildfire models is contributed by the TREEADS partners as well as information on the wildfire model scope (prevention, preparedness, detection, response, restoration, and adaptation), wildfire model type (empirical, semi-empirical and physical wildfire model), input data and type, the outcome of the model, potential standards related to the model, the relevant WP2 requirements related to this model, the use cases/pilots of TREEADS where this model will be applied and the involved TREEADS partners.

BAM WILDFIRE MODELS

BAM considers the fire dynamics simulator software to model fire and smoke propagation using partial differential equations. The focus of their model is prevention, preparedness and response, and the model itself falls under the physical category. Several inputs are required for the successful operation of the model, for example fuel material parameter, typically elicited from real fire tests and adjusted appropriately, given the parameters of each use case scenario. It is worth mentioning that BAM's model supports combustible solids and liquids alike, through a pyrolysis sub model.

Table 4 BAM: Fire Dynamics Simulator FDS

Fire Dynamics Simulator FDS	
Wildfire Model Description	Computational Fluid Dynamics describes the methods of of numerical fluid mechanics is based on the discrete solutions of the Navier-Stokes equations to describe frictional flows. Flow phenomena are described with partial differential equations partial differential equations. Modeling of fire and smoke propagation requires the solution of partial differential equations (PDGL). These are in most cases no longer analytically solvable the PDGL must be transformed into a system of discretisation method into a system of algebraic equations. FDS is a field model which is based on the finite difference method (second order accurate in space and time). Its discretisation is based on a rectangular grid. All objects included need to be integrated into the basic cell grid adopted. Main features of the Fire Dynamic Simulator concerning fire modelling are the sub models for involving combustion, heat radiation and flow turbulence. The combustion model is based on the mixture fraction approach. In detail the mixture fraction is a scalar quantity defined as a fraction of gas at a point in the flow field that originates from

	fuel. This approach also includes heat and smoke production due to the combustion reaction. Principally the mixture fraction combustion approach assumes infinitely fast combustion reactions and controlled mixing of fuel and oxygen in the combustion processes. As an essential input for gas phase modelling the rates of reactants and products need to be established for the chemical reaction equation For combustible solids and liquids a pyrolysis sub model is also included in FDS. This pyrolysis model is based on the solution of an one-dimensional heat transfer equation and can be applied on boundary surfaces of the flow field. In a submodel of the pyrolysis model the material surface can be composed of different layers consisting of diverse components. In solids the heat transfer is calculated by using a function which incorporates the composition of material layers and their thermal properties. Fundamentally reaction products are differentiated in water vapour, fuel and residues. Water vapour and fuel are immediately absorbed by adjacent cells of flow field when getting produced. Residues remain in its initial solid. The Fire Dynamic Simulator contains also a sub model for radiative heat transfer for which mainly the solution of the radiation transport equation for grey gases makes allowance for. Grey gases mean the fluid which is irradiated by heat radiation and in which (independently from the related wavelength) emission and absorption of radiation occurs. The radiation transport equation is based on a method similar to the Finite Volume Method (FVM), in which the same grid as applied for the flow computations is used.
Wildfire Model Scope	Prevention, Preparedness, Response,
Wildfire Model Type	Physical Wildfire Model
Input Data and Type	For preparing fire simulations material parameters are essentially needed to complete. Material data of typical bus materials were already established while examining their fire behaviour in fire experiments (WP2, WP 8). However, using raw material data from corresponding fire tests only are not expedient for fire simulations. Before implementing those in a fire model they need to be verified by simple simulations in order to adjust them.
Outcome	Temperature, velocity, soot fraction, smoke gas components, heat release rate in each grid point of the computational domain

Standards	ISO/DTR 24188 Large outdoor fires and the built environment, Global overview of different approaches for standardisation; ISO13571 Life-threatening components of fire - Guidelines for the estimation of time to compromised tenability in fires; ISO 13344:2015 Estimation of the lethal toxic potency of fire effluents; ISO 19701:2013 Methods for sampling and analysis of fire effluents; ISO 19702:2015 Guidance for sampling and analysis of toxic gases and vapours in fire effluents using Fourier Transform Infrared (FTIR) spectroscopy models for obtaining fire effluent toxicity data for fire hazard and risk assessment — Part 2: Evaluation of individual physical fire models ISO/TR 16312-2:2021 Guidance for assessing the validity of physical fire models for obtaining fire effluent toxicity data for fire hazard and risk assessment — Part 2: Evaluation of individual physical fire models
Relevant WP2 Requirements	FR-PROC1-9: To predict the spread of fire and smoke FR-OUT3-5: Prediction of the spread of fire and smoke
Use Cases / Pilots	Task 8.5: Pilot use case 4: Spanish pilot Task 8.6: Pilot use case 5: Austrian pilot Task 8.7: Pilot use case 6: German pilot
Involved TREEADS Partners	OVGU: small and real-scale experiments to share the results as input parameters for CFD simulations, USAL: wind field model, atmospheric pollutants dispersion model, forest fire spread simulation USAL: wind field model, atmospheric pollutants dispersion model, forest fire spread simulation
Advancements compared to existing models	The fire spread mechanisms in the ground of forests are not yet fully understood. Especially, the influence of the local vegetations and of different local vegetations are not addressed yet. In FDS the wildfire simulation tool is one of the most advanced tools in fire research as it takes the physical and chemical processes into account. However, the mostly used parameters for vegetation are standard parameters which take not local vegetation into account. The model will be updated with the experimental data from small, medium and large-scale tests in the project with local vegetation. Therefore, the model will be improved significantly compared with the state of the art.

Utilisation of existing models	The WFDS model of FDS is used and adjusted to the needs of predictions for the model regions of the German pilot Saxony-Anhalt and Brandenburg. This is done by vast experimental data for local vegetation created during the project. Validation of the models is done by comparing the predictions of the models with the results of medium and large-scale tests.
Beyond current knowledge and practice	Countries as USA and Australia have advanced research in simulation of wildfires. However, often the simulation is done on a very large scale without taking the physical and chemical processes into account. The local vegetation is not comparable as for instance eucalyptus trees are a major fire thread in Australia with significant differences in fire behaviour than the local vegetation in the German model regions. In the German model regions pine trees are very common but oak and beech are also present. Most fires in the model regions of the German pilot are ground fires in contrast to tree or crown fires in the US and Australia. Therefore, the mechanism and speed of fire spread is significantly different. Predictions can only be successful with taking the local vegetation into account.
Beyond current TRL	FDS wildfire models used so far are not adjusted to local vegetation in Germany. As the local vegetation and the means of fire spread are very specific in the German model regions an adjustment of the FDS wildfire models will provide better predictions of wildfires and will enhance the understanding of fire spread mechanisms for prevention, preparation of first responders and fire fighting tactics.

CARTIF WILDFIRE MODELS

CARTIF will create a model that will utilise data mining in combination with Copernicus and time-series, linking datasets across scales with high/medium spatial resolution. Computer vision AI technics are to applied for identification of wild fires risk. The model will also provide an early warning on potential natural disasters, based on the monitoring of the vegetation cover and other features from the imagery available.

Table 5 CARTIF: Earth Observation model for Fire Exposure and Risk assessment

Earth Observation model for Fire Exposure and Risk assessment	
Wildfire Model Description	Using Copernicus services and their time series provided, a wildfire model (using Deep Learning techniques) that offers services related to forest fire exposure and risk estimation will be released. This model will be implemented in this way:

	(1) The model will be designed using a combination of ConvNeXt and LSTM/GRU networks and it will be trained using the available data: vegetation conditions (vegetation fuel types, vegetation moisture conditions), terrain conditions, weather conditions of the targeted territory. The information gathered in existing municipal prevention plans will be assessed during the specification of the risk. (2) The model will periodically estimate the exposure of a certain village and/or assets to forest fire using previously trained neural networks. (3) The model will also provide an early warning on potential natural disasters, based on the monitoring of the vegetation cover and other features from the imagery available. The diversity of imagery sources would provide different levels of warnings: from drought alerts on wide or regional areas to the detection of new construction or activities on protected areas.
Wildfire Model Scope	Prevention, Preparedness
Wildfire Model Type	Empirical Wildfire Model
Input Data and Type	Sentinel-1, 2 & 3 images MODIS data LST data Corine Land Cover IGN data (Spanish provider) Miteco EGIF data (Spanish provider) Junta de Castilla y León data: Open Data, Infocal... (Spanish provider)
Outcome	Fire exposure of a certain village
Standards	INSPIRE Directive
Relevant WP2 Requirements	FR-IN2-7: The system must be able to obtain, store and manage information from Copernicus Services FR-CONF2-1: To provide times of danger based on general forecast and custom on-premise parameters FR-CONF2-2: to set up custom metrics and KPI´s FR-CONF2-5: To generate data sources to feed prediction models FR-PROC1-17: As a decision support system FR-OUT2-3: Vulnerability per area information
Use Cases / Pilots	Spanish pilot (4)
Involved TREEADS Partners	<CARTIF>: Design, train and refine the model. Results analysis

	<USAL> will integrate the results of the model in the TREEADS platform to make them accessible to other interested partners
Advancements compared to existing models	The tool integrates meteorological observations and forecasts with vegetation cover and topography to produce fire risk maps, but with a more detailed spatial, temporal and process description compared to existing models.
Utilisation of existing models	The new model is based on the ECMWF climate prediction and increases the detail of the fire risk prediction by intensifying the grid to one square kilometre, considering that this resolution is also provided by the recently published European fuel model (FirEUrisk project), adding the Copernicus digital terrain model with a 25 m grid.
Beyond current knowledge and practice	The system adds more information to improve its capability to capture the spatial distribution of risk and the effect of vegetation. In addition to daily updated meteorological and satellite data, the algorithm uses a digital elevation model, satellite (historical data) vegetation conditions and fuel mapping. These capabilities will be also enhanced by the use of different data collection systems based on the 4-layer approach.
Beyond current TRL	Currently, the TRL can be considered as a 4, and after its application in the pilots, it will be possible to complete the validation of the developed system and to think about one or two steps forward in the TRL scale.

Table 6 CARTIF: Territorial assessment model to evaluate climate related risks and vulnerabilities

Territorial assessment model to evaluate climate related risks and vulnerabilities	
Wildfire Model Description	This Climate model will be based on Copernicus services and the main objective is to identify the baseline of main vulnerabilities and threats in a specific territory to estimate the associated risk. This service is compound by Deep Learning analytics to identify metrics and KPIs related to existing territorial vulnerabilities and threats (baseline and projections). This model is based on AI and computer vision technics mainly applied to Sentinel imagery.
Wildfire Model Scope	Prevention, Preparedness
Wildfire Model Type	Empirical Wildfire Model

Input Data and Type	Sentinel-1&2 images Corine Land Cover Junta de Castilla y León data (Spanish provider)
Outcome	Vulnerabilities and threats in a specific territory
Standards	INSPIRE Directive
Relevant WP2 Requirements	FR-IN2-7: The system must be able to obtain, store and manage information from Copernicus Services FR-PROC1-10: To enhance sensors retrieved information using information from other sources FR-CONF2-1: To provide times of danger based on general forecast and custom on premise parameters FR-CONF2-2: to set up custom metrics and KPI´s FR-CONF2-5: To generate data sources to feed prediction models FR-OUT2-3: Vulnerability per area information
Use Cases / Pilots	Spanish pilot (4)
Involved TREEADS Partners	<CARTIF>: Design, train and refine the model. Results analysis <USAL> will integrate the results of the model in the TREEADS platform to make them accessible to other interested partners
Advancements compared to existing models	This tool proposes the use of new segmentation techniques from satellite imagery to more accurately identify infrastructure, the wildland-urban interface and fuel type, and to help identify metrics at the local level.
Utilisation of existing models	This model is based on AI and computer vision techniques mainly applied to Sentinel imagery.
Beyond current knowledge and practice	The proposed models will explore the use of advanced segmentation techniques in an area where they have not been applied before. Different techniques such as SAM (Segment Anything Model) will be analysed. SAM's advanced design allows it to adapt to new image distributions and tasks without the need for prior knowledge, a feature known as zero-shot transfer. It has been trained on the extensive SA-1B dataset, which contains more than a billion masks spread over 11 million carefully selected images.

Beyond current TRL	Currently, the TRL can be considered as a 4, and after its application in the pilots, it will be possible to complete the validation of the developed system and to think about one or two steps forward in the scale.

NOA WILDFIRE MODELS

NOA's role would provide fire risk maps for the area of interest and an uncertainty estimate for the predictions as well as a burnt scar mapping model that will exploit remote sensing data and AI techniques in order to assess the perimeter of the affected area after a wildfire event. The models utilise MODIS, ERA5-Land, CLC, EU-DEM, JRC, worlpdpop.org, Sentinel-2 and databases such as BARD.

Table 7 NOA: Fire risk prediction Model

Fire risk prediction Model	
Wildfire Model Description	Wildfire model will provide fire risk maps for the area of interest as well as an uncertainty estimate for the predictions. Several inputs will be used like vegetation status, satellite variables, weather forecasts, anthropogenic factors. The goal is to use a time-series of these variables to estimate the fire risk. The inputs will be passed through a Bayesian Deep Learning model that will be trained in a supervised way to provide the fire danger for the next day or next week for the area of interest in a good spatial resolution. The labels for the training will be the burned areas that have been generated by large fires. Using Bayesian Deep Learning, the goal is to also provide uncertainty estimates for the predictions (i.e. provide also information about how confident the model is for its output). The predictions of the model will be potentially used for fire management activities and action from the authorities. So, having uncertainty estimates for the outputs can play a significant role in better understanding the problem and help in better decision making.
Wildfire Model Scope	Prevention, Preparedness
Wildfire Model Type	Data-driven Wildfire Model
Input Data and Type	Land Surface Temperature (MODIS) Vegetation Indices (MODIS) Weather data (precipitation, humidity, wind, temperature) (ERA5-Land) Land Cover (CLC) Elevation (EU-DEM)

	Soil Moisture (JRC) Population Density (worldpop.org) Distance to Roads (worlpdpop.org)
Outcome	Daily/weekly fire risk maps, Uncertainty estimates for the predictions.
Standards	-
Relevant WP2 Requirements	FR-OUT2-3: Vulnerability per area information FR-OUT-3-1: Multispectral images on demand
Use Cases / Pilots	Use Case 2 / Pilot 4 Use Case 2 / Pilot 7
Involved TREEADS Partners	**DdA**: DdA will use this model in order to assess the predicted fire danger and manage prevention plans accordingly. **TUC**: TUC will use this model for assembling/improving fire protection plans. **MAICh**: MAICh will use this model for assembling/improving fire protection plans. **DAAC**: DAAC will use this model for assembling/improving fire protection plans.
Advancements compared to existing models	In the realm of fire prediction, various methods exist in the literature. Traditional models such as the Fire Weather Index focus on forecasting wildfire risk primarily based on meteorological variables while overlooking the intricate interplay between all the factors that contribute to fire occurrence. Other approaches include traditional machine learning models like Random Forest and Logistic Regression. More recently, researchers have delved into the realm of deep learning, employing techniques such as Long Short-Term Memory (LSTMs) Neural Networks and Convolutional Neural Networks (CNNs) to capture the spatial and temporal dynamics among the diverse fire drivers. Nonetheless, these models tend to overlook the inherent uncertainty in their predictions. In TREEADS project, we propose to build upon existing solutions by developing Bayesian Deep Learning models that not only make predictions but also incorporate and forecast the associated uncertainty. Furthermore, recognizing that wildfire danger forecasting often involves dealing with noisy labels during model development, we aim to devise methodologies that account for this noise, thereby predicting aleatoric uncertainty as well. These innovative

	approaches represent a significant advancement in the domain of data-driven wildfire modelling.
Utilisation of existing models	As previously mentioned, our research in Bayesian Deep Learning will build upon established deep learning models' architectures, such as LSTMs and CNNs. We will enhance these deterministic models by introducing components that account for and model uncertainty. This endeavour involves the adaptation of LSTMs and CNNs and maybe other existing architectures to capture not only the primary patterns and features in the data but also the associated uncertainty in a coherent and informative manner. Moreover, we will use already existing Bayesian modelling techniques to capture this uncertainty like Deep Ensembles, Dropout methods and several probabilistic ML approaches.
Beyond current knowledge and practice	Our approach will shed light on 1. what models know that they know and 2. what models know that they do not know. Moreover, the uncertainty of the predictions that we are going to provide will enhance the trustworthiness and reliability of the predictions, thus improving wildfire decision-making and management. Finally, we will make research on a new field (Bayesian Deep Learning on Wildfire Forecasting) that we hope that will pave the way to significant improvements in the field.
Beyond current TRL	Our solution for fire danger prediction starts from TRL 4 and is expected to reach TRL 6.

Table 8 NOA: Burnt Scar Mapping Model

Burnt Scar Mapping Model	
Wildfire Model Description	The burnt scar mapping model will exploit Remote Sensing data and AI techniques in order to assess the perimeter of the affected area after a wildfire event. In particular, it will employ Deep Learning approaches which have the ability to handle multi-modal, multi-dimensional data and past knowledge, and produce state-of-the-art results in several image processing tasks. Our goal is to utilise satellite imagery of multiple spatiotemporal resolution scales along with auxiliary data such as DEMs, land cover maps, etc, in order to produce a daily binary mask of the burnt area in a high spatial resolution. The labels for the training will be the burnt areas that have been generated by large fires. The model will be trained on historical fire events in the region of Greece and tested on different events in Greece and/or other countries, depending on label availability.

Wildfire Model Scope	Restoration and Adaptation
Wildfire Model Type	Empirical Wildfire Model
Input Data and Type	The labels of the model are provided by NOA. Other public databases such as BARD [1] may also be used. The input will be Sentinel-2 and MODIS multispectral satellite imagery, and possibly also DEMs and land cover maps. Other assisting data inputs will be explored.
Outcome	The output of our model will be a binary image map of the burnt scar. It will be produced within 1-2 days after a wildfire event and several maps can be produced in a day (quality will be affected by possible cloud contamination).
Standards	-
Relevant WP2 Requirements	FR-PROC-1-23: To obtain real-time environmental impact caused by fire reports FR-OUT-3-1: Multispectral images on demand
Use Cases / Pilots	Use Case 2 / Pilot 4 Use Case 2 / Pilot 7
Involved TREEADS Partners	**DdA**: DdA will use this model in order to assess the damage inflicted by the wildfire event and plan next actions for environmental restoration and community relief. **TUC**: TUC will use this model for fire incident environmental impact assessment and/or development of a site-specific post-wildfire good practice handbook. **MAICh**: MAICh will use this model for fire incident environmental impact assessment and/or development of a site-specific post-wildfire good practice handbook. **DAAC**: DAAC will use this model for fire incident environmental impact assessment and/or development of a site-specific post-wildfire good practice handbook.
Advancements compared to existing models	Various methods have been proposed in the literature for the automatic mapping of burnt areas. The most common approach is the computation of specialized spectral indices, such as Normalized Burn Ratio, Mid-Infrared Burn Index, etc. However, these indices are prone to commission errors and confusion with structures presenting spectral signatures similar to burnt land. In addition, they struggle to generalize to different land covers, biomes and atmospheric conditions. Another popular approach for the task of burn scar mapping is the use of traditional Machine Learning algorithms such as Random Forest, Support Vector Machine, etc. These methods have been heavily examined in the literature but

	they require heavy feature engineering processes and the final predictions are usually quite noisy. Finally, a number of Deep Learning techniques have recently been proposed in order to alleviate the shortcomings of the previous methods and achieve better mappings. Deep Learning models are able to handle raw input data and deliver state-of-the-art results with minimal human intervention. However, after a thorough investigation of the literature, we find that the existing models are either trained and evaluated on single events, thus their generalization ability is not concretely established, or require only post-fire imagery, which makes them prone to spectral confusion and misclassification of older burn scars. Finally, most models are not publicly available to the community so it is difficult to use them and assess their performance. Our proposed model tackles the problem of burn scar mapping effectively and achieves state-of-the-art results surpassing the commonly used methods we compared against. It requires a pre-fire and a post-fire high resolution multispectral image in the input (coming from Sentinel-2) and produces sharp mappings of the perimeter of the burnt area with minimum errors. It is also released as open source in order to be a useful asset to the wider community.
Utilisation of existing models	Although our proposed model is not directly based on existing Deep Learning models for burn scar mapping, it employs techniques from the more generic domain of change detection. In particular, we design a novel architecture which comprises a dual-branch encoder with a ResNet-101 backbone, a U-Net structure and attention modules in the decoder.
Beyond current knowledge and practice	Our model provides a fully automated way of burnt area mapping, which does not require human intervention. In addition, it can generalize without significant errors.
Beyond current TRL	Our solution for burnt area mapping starts from TRL 5 and is expected to reach TRL 7.

OVGU WILDFIRE MODELS

OVGU resorts to the usage of a physical wildfire model utilising numerical simulation of turbulent fluid flows and heat/mass transfer along with chemical reactions to build a fluid mechanics-based model with the ANSYS CFX software. OVGU's model will utilise geometry data, physical and chemical material properties of vegetation, ambient conditions (i.e., temperature, air conditions, pressure, and humidity), as well as burning rates to implement modelling focusing on prevention, preparedness, and response.

Table 9 OVGU: ANSYS CFX

ANSYS CFX	

Wildfire Model Description	The numerical simulation of turbulent fluid flows as well as the heat and mass transfer and chemical reactions are based on physical models of fluid mechanics. The fundamental equations of numerical fluid computation are the continuity equation (conservation of mass), the Navier-Stokes equations (conservation of momentum), the energy equation (conservation of energy) and the turbulence equations.
	CFX is a general fluid flow program to solve three-dimensional friction flows with heat transfer. For discretisation ANSYS CFX uses the finite volume method to treat the transport phenomena like convection, diffusion and source. It allows the conversion of the integrated governing equations for each control volume in a system of algebraic equations, which can be solved with iterative methods.
	Short summary:
	• CFX is a general fluid flow program to solve three-dimensional friction flows with heat transfer
	• Computational Fluid Dynamics = describes the methods of numerical fluid mechanics
	• CFD is based on the discrete solutions of the Navier-Stokes equations (conservation of momentum) and conservation of mass and energy to describe frictional flows with heat transfer
	• flow phenomena are described with partial differential equations
	• modeling of fire and smoke propagation requires the solution of partial differential equations (PDE)
	• these are in most cases no longer analytically solvable the PDGL must be transformed into a system of discretization method into a system of algebraic equations
	• iterative numerical solution
	• Pre-selection of physical models:
	  ○ EDM = Eddy Dissipation Model (Combustion Model)
	  ○ SST = Shear Stress Transport (Turbulence Model)
	  ○ MC = Monte Carlo (Radiation Model)
	Clarification:
	Combination of experimental and numerical investigation will be used to understand the fire behavior of vegetation, especially for fires moving in the ground. Experiments of

	specimens of forest and grassland ground specimens with a variation of parameters is the basis for detailed modelling of the mechanisms. Small and mediums scale experiments are the basis to develop a numerical model capable of predicting the fire propagation. The large-scale experiments will be used to validate the numerical models. The combination of experiments and numerical investigation allows a quantitative assessment of the influence of the different heat transfer modes and therefore will significantly improve the understanding of fire propagation in these fires.
Wildfire Model Scope	Prevention, Preparedness, Response
Wildfire Model Type	Physical Wildfire Model
Input Data and Type	Geometry data, physico-chemical material properties of typical vegetation, ambient conditions (ambient temperature, ambient air conditions, pressure, relative humidity), combustion reaction equations, mass burning rates
Outcome	temperatures, mass fractions of smoke gas species, soot fraction, velocities, pressure, flame heights, flame thickness, Fractional Effective Dose for the evaluation of smoke gas toxicity
Standards	**ISO13571** Life-threatening components of fire - Guidelines for the estimation of time to compromised tenability in fires **ISO/DTR 24188** Large outdoor fires and the built environment, Global overview of different approaches for standardisation **ISO 13344:2015** Estimation of the lethal toxic potency of fire effluents **ISO 19701:2013** Methods for sampling and analysis of fire effluents **ISO 19702:2015** Guidance for sampling and analysis of toxic gases and vapours in fire effluents using Fourier Transform Infrared (FTIR) spectroscopy **ISO/TR 16312-2:2021** Guidance for assessing the validity of physical fire models for obtaining fire effluent toxicity data for fire hazard and risk assessment — Part 2: Evaluation of individual physical fire models
Relevant WP2 Requirements	FR-PROC1-9: To predict the spread of fire and smoke FR-OUT3-5: Prediction of the spread of fire and smoke
Use Cases / Pilots	Task 8.5: Pilot use case 4: Spanish pilot Task 8.6: Pilot use case 5: Austria pilot Task 8.7: Pilot use case 6: German pilot

Involved TREEADS Partners	**BAM:** small and real-scale experiments to share the results as input parameters for CFD simulations **USAL:** wind field model, atmospheric pollutants dispersion model, forest fire spread simulation
Advancements compared to existing models	Current fire spread models consider the horizontal spread of fire, but not the long-lasting (>24h) vertical, smoldering spread of fire in the ground (porous media) through different layers. The numerical modelling of smoldering combustion is intended to simulate the non-flaming fire spread in vegetation typical for Germany. The development of advanced numerical approaches for estimating and predicting wildland fire and their phenomena using the methods of Computational Fluid Dynamics, respectively the general fluid flow code ANSYS CFX is the point of going beyond in comparison of existing models. The challenge here is to use all the data already recorded from small-scale fire tests (e.g. DIN tube furnace, hot storage furnace etc.), from material analysis (e.g. heat of combustion, organic content, chemical composition etc.) and from real-scale fire tests (already carried out in Pilot region) in order to include cross-scale data in the modeling of the fire phenomena (turbulence, transition smoldering to flaming, dispersion of smoke gases in dependence of meteorological influences among others).
Utilisation of existing models	To simulate the smoldering combustion, the set up in ANSYS looks like à geometry creation, meshing, pre-processing, solver, post-processing. Ansys CFX is not a wildfire model per se, but uses the theory of computational fluid dynamics and is a deterministic model based on physical laws. The modelling approach in Ansys CFX is based on the set-up and combination of different models for energy and mass transport and momentum flow as well as species concentrations for chemical processes. These include specialized modules for heat transport, fluid mechanics, thermal reactions and other relevant physical processes. The material (ground vegetation in layers) is defined in terms of their properties: density, porosity, heat capacity, thermal conductivity, decomposition temperatures, reaction kinetics, Moisture Content etc. The input parameters are determined by comprehensive laboratory studies and literature research.
Beyond current knowledge and practice	The focus is on the temporary long fire propagation in the ground, behind the flame front, which is usually neglected in the horizontal fire propagation. In addition, there is a lack of

	simulations of the German vegetation and the specific composition as well as the characterization of the typical combustion phenomena. Through the selective use of these diverse models in ANSYS, we can develop a customized and detailed simulation in in relation to the identified problems of the German Pilot. The simulation is intended to provide the following results: • Temperature distribution in the computational domain • Velocities as well as species concentration • propagation and behavior of the fire (direction, speed, intensity) • Heat release rate during the fire • Prediction of the composition and spread of smoke • Assessment of harmful concentrations of smoke gases using toxicity models The aim is to characterize the types of fire that occur in relation to vegetation fires as well as to identify significant influencing factors for fire development. Numerical and experimental research on vegetation and forest fires is intended to close gaps in knowledge about the chemical processes in progress and how the fire starts and spreads, considering climate and topographical influences.
Beyond current TRL	The simulation goes beyond the TRL, as it combines the findings from laboratory and small-scale experiments in regard to long smoldering ground fires by setting-up a comprehensive numerical modelling approach using the methods of Computational Fluid Dynamics (CFD). The results of the laboratory tests form the basis for the physio-chemical input parameters and boundary conditions. By processing the data of the large-scale fire tests of vegetation specific to Germany, the fire propagation simulation can be validated. First and foremost, our chosen modeling approach is intended as a numerical experiment to identify possible fire phenomena on large scales and to understand the physics of a forest fire or vegetation fire as adequately as possible - this ranges from mass burning and energy release to smoke gas composition and dispersion. More detailed description of work done in the German Pilot can found in the updated WP8 Deliverable.

SQD WILDFIRE MODELS

SQD leads Task 6.3: TREEADS Involvement, coordination, and cooperation of different actors and sectors. The models used in this framework will be detection algorithms for events and activity monitoring tools, integrated in the platform. Within this framework several proposed models will be tested, which will include multi-temporal processing methods for improving visualisation to complex behaviour processing methods that are taking into account all related communities' attribution and reasoning. The main categories of the models will include linear models, ML/AI models and fussy logic models for decision making.

Table 10 SQD: SOCIO-TECHNOLOGICAL Solution for Restoration and Adaptation Model

SOCIO-TECHNOLOGICAL Solution for Restoration and Adaptation	
Wildfire Model Description	**Framework SOCIO-TECHNOLOGICAL Solution for Restoration and Adaptation (SQD, Task 6.3):** The unified co-operation framework will enable end-user agencies to handle the tactical, strategic and operational activities. Within this context a geospatial data infrastructure solution will be developed using Web-GIS and spatially enabled web portals. The purpose will be the integration, visualisation and assessment of all the data inputs. The models used in this framework will be detection algorithms for events and activity monitoring tools, integrated in the platform. It will also include the system of the Task 6.2. with the intelligent mechanisms for self-adaptation to the scenario in a user-friendly way. Within this framework several proposed models will be tested, which will include multi-temporal processing methods for improving visualisation to complex behaviour processing methods that are taking into account all related communities' attribution and reasoning. The main categories of the models will include linear models, ML/AI models and fussy logic models for decision making. To achieve the scalability of the platform, given the large amount of data inputs, a decision support system (DSS) will be encompassed with intelligent mechanisms for analysing the monitoring data stemming from the control & management and data planes of the TREEADS Sensors Network.
Wildfire Model Scope	Restoration and Adaptation
Wildfire Model Type	Empirical Wildfire Model/Framework
Input Data and Type	This framework will use Satellite, UAV and ground datasets. In the beginning, further data will be also used such as weather and lightning data, as well as outputs from certain indicators, that the corresponding partners will define for the restoration and adaption process. These data concern

	the initial training and implementations testing of the models. With the maturity of the project and the availability of TREEADS technology, the model will use data coming from the project's drones and sensors.
Outcome	The outcome will be certain indicators, visualisations and information dashboards that the corresponding partners will define, regarding restoration and adaptation that are necessary to the end-users.
Linked Deliverables & Milestones	D6.1 to D6.3: TREEADS SOCIO-TECHNOLOGICAL Solution for Restoration and Adaptation v1-3 MS5 First version of TREEADS risk management, services & modules prototype completed MS7 First set of TREEADS Holist fire management Ecosystem prototypes completed and MS13 Final version of TREEADS Holist fire management Ecosystem prototypes completed
Standards	Not yet specified precisely will focus on the specific finalised requirements.
Relevant WP2 Requirements	*Requirements are indicative, need further discussions with the partners to provide a more robust picture about the finalised requirements.*
Use Cases / Pilots	Not yet specified.
Involved TREEADS Partners	**SQD,** ALTRAN, UdG, ACCELI, GBD, LAMMC, BFG, FAFCYLE, DdA, TUC
Advancements compared to existing models	The combination of the restoration solutions in the DSS is an advancement that will give the stakeholders a novel set of tools and services that will save them time and help them cooperate and achieve results that were previously not possible. Manual intensive work such as using specific programs that require a lot of configuration and time in order to achieve the desired outcome will be streamlined, providing results that are very accurate and provide results with less errors, as the human error is removed from the equation. The processing and unification of all the related datasets will be a novelty as well and an advancements, especially for the specific Pilots that are interested and involved with the DSS.
Utilisation of existing models	Existing algorithms that are Open Source are used but are then customized to fulfil the needs of the Task. Such models and algorithms involve models that calculate the Fire Severity and other information layers that help the coordination of the stakeholders and involved partis. Most

	of the work is original in its essence with similar workflow to existing work. No specific AI/ML model is utilized to be mentioned.
Beyond current knowledge and practice	The provision of streamlined pipelines to provide the informational layers and decision-making proposed actions goes beyond the current practice, in terms of gathering everything in a unified solution. This will enable the development of knowledge and focus on the steps ahead, for example an emphasis on the different decision-making approach and methodology instead of only the provision of initial information.
Beyond current TRL	The tool will beyond the current TRL as it will advance from a formulated concept to an application validated in a relevant environment and beyond. The application will be tested in relevant Pilots and the functionality and importance of the DSS will be validated this way.

TUC WILDFIRE MODELS

TUC leads Task 6.1: TREEADS Artificial intelligent Soil assessment, Agroforestry and Soil Enhancements and automation. As part of this task TUC will provide a model for evaluating indicators for soil assessment with UAVs. The ability to utilise aerial mean in the soil assessment will enable the use of evaluating indicators. This indicator will be physical, chemical or characteristics of the soil e.g., Ph, Alkaline, Nitrogen etc. Once this indicator is gathered and based on data stemming from the TREEADS sensors data, weather data, map spectrograph etc the TREEADS system will be able to use drones in order to enhance the soil and on the same time to break the subjective current approach that is used in soil assessment by utilising Artificial intelligence federated learning. TREEADS also utilise Agroforestry techniques for restoring land back to health by using methods from agroforestry including rotational grazing of livestock and recycling forest waste into biochar.

Table 11 TUC: Soil assessment model

Soil assessment model	
Wildfire Model Description	**Agroforestry for restoration (TUC, Task 6.1): Artificial intelligent Soil assessment, Agroforestry and Soil Enhancements and automation** This model will make use of LMA to provide aerial images to evaluate indicators for soil assessment. Those indicators will be physical, chemical or general soil characteristics such as pH, Alkaline, Nitrogen etc. As long as those indicators are evaluated using multiple data, an Artificial Intelligence

	approach will be used to assess the soil, breaking the subjective approaches used so far.
Wildfire Model Scope	Restoration and Adaptation
Wildfire Model Type	Empirical Wildfire Model
Input Data and Type	This model will use aerial image datasets for the implementations of the first iterations of the models.
Outcome	The outcome will be certain indicators that the corresponding partners will define, regarding soil properties and characteristics, that are necessary for the development of their technologies. From the soil assessment the service will be able to provide a set of appropriate agroforestry restoration techniques.
Standards	Not yet specified.
Relevant WP2 Requirements	*Requirements are indicative, need further discussions with the partners to provide a more robust picture about the finalised requirements.* **FR-IN1-2**: From infrared cameras/optical sensors **FR-IN1-3**: From multispectral cameras **FR-IN1-4**: From thermal cameras **FR-IN1-6**: From soil humidity sensors **FR-IN2-5**: From Copernicus Services - satellite data **FR-IN2-6**: From weather information services **FR-DAT3-1**: Drones **FR-DAT5-3**: Data on characterised soil **FR-PROC1-7**: To obtain soil and vegetation terrain information **FR-PROC1-8**: To enhance sensors retrieved information using information from other sources **FR-PROC1-9**: To optimise post-fire restoration strategies
Use Cases / Pilots	Not yet specified.
Involved TREEADS Partners	<**TUC**>: Leader of the task and developer of the model <**SQD**>: WP6 coordinator, will take part in the integration of the model into the TREEADS platform <**GBD**>: Will use the outcome, the soil specific indicators for the development of their Task (Task 6.2) <**LAMMC**>: Will use the outcome, the soil specific indicators for the development of their Task (Task 6.2) <**UdG**>: Will provide useful information for the Agroforestry techniques for restoring land back to health
Advancements compared to existing models	This model will be able to provide very high resolution (<1 meter) spatial information, and provide valuable

	information to stakeholders, regarding appropriate agroforestry restoration practices.
Utilisation of existing models	Many existing scientific models and methodologies have been studied, but so far there is no existing model that will be used or will be based on.
Beyond current knowledge and practice	The proposed model aims to create a pipeline for a quick assessment of soil condition after a wildfire event. This state-of-the-art model, will be able to take input from very high-resolution remote sensing images coming from sensors that are widely available in the scientific and industry domain. Also, there is no model that utilises this kind of specific information to provide a decision-making approach to aid stakeholders on restoration efforts.
Beyond current TRL	This model is introduced and is being developed entirely within TREEADS (from TRL of 1)

USAL WILDFIRE MODELS

USAL provides three ecological and environmental wildfire models: the physical forest fire spread model PhyFire, the high resolution wind field model HDWind, and the atmospheric pollutant dispersion model PhyNX. PhyFire provides near real time simulation of wildfire with a simplified physical wildfire spread model and it can aid in forest fire prevention for risk map designing; During the evolution of a forest fire, simulation can be used as a tool to support the complex process of decision-making, as well as to make an ex post analysis. HDWind could reliably provide meteorological data, mainly wind data, for predicting a forest fire spread. PhyNX could contribute in forecasting simulation of fire smoke cloud dispersion.

Table 12 USAL: PhyFire Model

PhyFire Description	
Wildfire Model	The PhyFire model is a simplified 2D one-phase physical wildfire spread model based on the energy and mass conservation laws. This model considers the two dominant thermal transfer mechanisms in wildfires, convection and radiation. It takes into account heat loss by natural convection, the effect of wind or slope on the flame tilt, and the influence of fuel moisture content and fuel distribution and type. It has the option of incorporating random phenomena such as fire spotting. It depends on meteorological data, that can be provided from measurements and/or forecasts from meteorological services. However, wind information can be improved

	through the use of the tool HDWind, which allows consideration of local effects from point and scattered wind data. It is a GIS embeddable model. The tool is prepared to update data during the simulation process, from meteorological data to intermediate perimeters, actions by firefighting teams or new sources of fire. To initiate the simulation process, the simulation area must be selected, and the needed spatial information and meteorological data of the simulation area must be provided. The level of precision must be determined, which varies from level precision 0 corresponding to 50 m cell size, to precision level 5, corresponding to 2.5 m cell size. The total simulation time and the number of intermediate outputs must be decided, taking into account that the process can be stopped to update the data (meteorological conditions, firebreaks, etc.) and relaunched again. The model depends on three parameters that affect convection, radiation and natural convection respectively.
Wildfire Model Scope	Prevention, Preparedness, Response
Wildfire Model Type	Physical Wildfire Model (Fire spread model)
Input Data and Type	The spatial information that this model requires is made up of three types of geographic data: a DEM, a fuel load distribution map and a land cover map (fuel type). Currently, it uses the Rothermel fuel classification, but can be adapted to another type of classification. It requires the following meteorological data: temperature, humidity and wind intensity and direction. The source of the fire must also be provided, be it a point, a line, an intermediate perimeter, etc.
Outcome	The model provides, at the selected time steps, the burned area, and the area that is burning, that is, not only the perimeter of the fire as a line but also the position and thickness of the fire front. It also provides the mass fraction of consumed fuel to feed the smoke diffusion model PhyNX.
Standards	ISO/DIS 19677(en): Guidelines for assessing the adverse impact of wildland fires on the environment and to people through environmental exposure
Relevant WP2 Requirements	FR-PROC1-9: To predict the spread of fire and smoke FR-OUT3-5: Prediction of the spread of fire and smoke
Use Cases / Pilots	Pilot 4 (Spain): Forest fire spread simulation Pilot 2 (Italy): Forest fire spread simulation

	Pilot 5 (Austria): Forest fire spread simulation Pilot 6 (Germany): Forest fire spread simulation Pilot 1 (Norway): Forest fire spread simulation
Involved TREEADS Partners	<**USAL**>: <Model development and GIS implementation>
Advancements compared to existing models	The existing commercial fire spread models currently in operation are mostly semi-empirical models, based on experience and intuition from past fires, and calibrated for the conditions in the areas for which they have been developed. The complex physical based models add a high computational cost. The proposed model attempts to preserve the advantages of physical models while maintaining a highly competitive computational cost thanks to the use of efficient numerical and computational methods. In addition, the model is ready to be integrated into any geographic information system, it supports any raster and vector format compatible with GDAL. Most existing models provide an approximation of the perimeter of the fire as an advancing line (the position of the perimeter), however PhyFire provides information on the burned area and the burning area (the extension of the active fire), as well as other useful outputs such as the heat release rate that stem directly from the use of a physics-based methodology.
Utilisation of existing models	We suggest the use of different fire spread models, including the proposed PhyFire model, to obtain fire spread probability maps as is done in weather forecasting.
Beyond current knowledge and practice	The aim is to adapt the model to the different European areas, with their vegetation characteristics and meteorological conditions, by simulating historical fires and planned prescribed burns, for an effective adjustment of the model parameters. As the model designers are part of the project, adaptations can be developed at the request of the end users in terms of visualisation of results and incorporation of new factors, e.g., how to take into account different types of firefighting actions in the simulation process.
Beyond current TRL	It is feasible to move from the current TRL 3-4 to a TRL 6 by carrying on an exhaustive model calibration and validation for which it is essential to have access to detailed and accurate data gathered from measurements of different magnitudes during the prescribed burns planned in the project. Regardless of the TRL level that can be reached, a general disclaimer must be added: all existing models are subject to errors and inaccuracies and may not accurately

	reflect the exact event due to numerous reasons: uncertainty of input data, limitations of the models, gaps in the understanding fire behaviour, uncertainty of weather predictions, etc.

Table 13 USAL: PhyNX Model

PhyNX	
Wildfire Model Description	The PhyNX model is an urban scale Eulerian non-reactive multilayer air pollution model, describing convection, turbulent diffusion and emission. The model equations are solved using an Adaptive Finite Element Method with characteristics in the horizontal directions and Finite Differences in the vertical direction and splitting techniques. Precision and computational costs are improved by parallel computing techniques. The wind field used in this air pollution model is provided by the HDWind model. The PhyNX model was initially designed for punctual emissions with no deposition, with the aim of providing pollutant concentration and Acute Exposure Guide Levels (AEGLs) values at different heights above ground. This model is currently being adapted to simulate the dispersion of smoke from forest fires by incorporating some important parameters: combustion efficiency, fuel moisture and emission factors, for the four most important components of smoke from forest fires: CO_2, CO, CH_4 and $PM_{2.5}$. It is a GIS embeddable model.
Wildfire Model Scope	Prevention, Preparedness, Response
Wildfire Model Type	Physical Wildfire Model (Smoke model)
Input Data and Type	To initiate the simulation process as a smoke diffusion model, the simulation area is defined during the PhyFire simulation, and the spatial data, the meteorological data, the mass fraction of consumed fuel from PhyFire, and eventually HDWind wind data, should be provided.
Outcome	The model will provide the concentration of CO_2, CO, CH_4 and $PM_{2.5}$ in the different air layers and for the selected time steps.
Standards	ISO/DIS 19677(en): Guidelines for assessing the adverse impact of wildland fires on the environment and to people through environmental exposure
Relevant WP2 Requirements	FR-PROC1-9: To predict the spread of fire and smoke FR-OUT3-5: Prediction of the spread of fire and smoke

Use Cases / Pilots	Pilot 4 (Spain): Atmospheric pollutants dispersion simulation Pilot 2 (Italy): Atmospheric pollutants dispersion simulation Pilot 5 (Austria): Atmospheric pollutants dispersion simulation Pilot 6 (Germany): Atmospheric pollutants dispersion simulation Pilot 1 (Norway): Atmospheric pollutants dispersion simulation
Involved TREEADS Partners	<**USAL**>: <Model development and GIS implementation>
Advancements compared to existing models	This pollutant dispersion model is coupled with the wind field model, which provides a high-resolution wind field at different heights, and with the fire spread model, which provides the smoke emission source, so that it can simulate the dispersion of smoke from a fire within a single integrated simulation system. Other existing smoke dispersion models work independently. PhyNX equations are solved with an efficient algorithm that allows to combine advanced numerical strategies and parallel computation. In addition, this model is also ready to be integrated into any geographic information system.
Utilisation of existing models	Bluesky Playground from the USDA can be used to compare results.
Beyond current knowledge and practice	The next essential step is to adjust the model parameters using parameter tuning techniques as long as reliable data on the quantity and composition of smoke clouds from real fires are available. The main parameters to be adjusted are combustion efficiency, emission coefficients, dispersion coefficients and reaction coefficients.
Beyond current TRL	The difficulty in improving the current TRL 3 lies in the lack of data on the quantity and composition of smoke clouds from fires, which are essential to adjust some of the model parameters mentioned above.

Table 14 USAL: HDWind Model

HDWind	
Wildfire Model Description	A crucial data for both the simulation of fire spread and the dispersion of emitted smoke is the wind. HDWind is the windfield model that tries to improve the available wind information and/or wind predictions by incorporating local

	orography and temperature effects and improves wind data inputs for PhyFire and PhyNX models. The HDWind model is a mass-consistent vertical diffusion wind field model, based on an asymptotic approximation of the primitive Navier-Stokes equations. The most salient feature of this asymptotic approach is that it provides a three-dimensional velocity wind field (which satisfies the incompressibility condition in the air layer) governed by a two-dimensional equation. Therefore, it can be coupled with the temperature surface distribution to account for thermal effects. Terrain slope, surface roughness and buoyancy forces are taken into account by the model. This model adjusts a three-dimensional velocity wind field in a layer under the influence of topography and temperature distribution, with a minimum computational cost. The wind velocity field obtained by the model is adjusted to several wind velocity measurements at different points in the 3D domain by solving an optimal control problem. These specific wind data can be known meteorological data or they can be predictions from some wind forecasting system such as WRF or HARMONIE-AROME, that is, the HDWind local model can be coupled with mesoscale predictive models to improve wind forecasts at the local level. The model depends on a single parameter, the friction coefficient, which is related to the surface roughness length. It is a GIS embeddable model.
Wildfire Model Scope	Prevention, Preparedness, Response
Wildfire Model Type	Physical Wildfire Model (Wind model)
Input Data and Type	To initiate the simulation process independently, the simulation area must be selected. The input data needed in the simulation area are topography, roughness, and surface temperature. A set of georeferenced point wind measurements (direction and intensity) in the simulation area is also needed. When this model is coupled with PhyFire of PhyNX, the simulation area and the corresponding cartographic and meteorological data are provided by these models.
Outcome	The model provides wind intensity and direction at each point of the simulation domain, which can be used in the models PhyFire and PhyNX as wind input data.
Standards	ISO/DIS 19677(en): Guidelines for assessing the adverse impact of wildland fires on the environment and to people through environmental exposure

Relevant WP2 Requirements	FR-PROC1-9: To predict the spread of fire and smoke FR-OUT3-5: Prediction of the spread of fire and smoke
Use Cases / Pilots	Pilot 4 (Spain): Wind field simulation Pilot 2 (Italy): Wind field simulation Pilot 5 (Austria): Wind field simulation Pilot 6 (Germany): Wind field simulation Pilot 1 (Norway): Wind field simulation
Involved TREEADS Partners	<**USAL**>: <Model development and GIS implementation>
Advancements compared to existing models	The commercial simulation tool that most resembles HDWind is WindNinja. Both simulators can provide spatially varying high resolution wind fields, using mesoscale wind data from weather station measurements or weather forecasting. But HDWind can provide results with better spatial resolution and at different heights, to supply wind data not only to the fire spread model but also to the smoke dispersion model. HDWind can provide a high-resolution 3D wind field that fits a scattered set of point data while keeping computational cost low, by means of a novel idea based on an asymptotic approximation of the vier Stokes equations. HDWind considers the effect of the slope and rugosity of the terrain over the local wind, but in addition it is also capable of taking into account the surface temperature thus making it able to calculate naturally occurring thermal convective currents. This model is also ready to be integrated into any geographic information system.
Utilisation of existing models	WindNinja can be used to compare the downscaling process for wind field simulation.
Beyond current knowledge and practice	A series of numerical experiments are planned to perform a global sensitivity analysis, evaluate the scale effect and adjust the parameters of the model, comparing with the WindNinja model and with real meteorological data.
Beyond current TRL	The current TRL 3-4 can be moved to a TRL 6 by means of comparing the simulated wind values to real measurements provided by weather stations.

CONCLUSIONS

The goal of this deliverable is to provide a roadmap about the TREEADS models and services that will be implemented within this project. Therefore, based on the requirements of WP2, three main categories of models and services are investigated based on the existing literature: (a) Prevention and Preparedness, (b) Detection and Response and (c) Restoration and Adaptation. Based on the outcomes of this analysis, the second goal of this report is to identify a first description and the attributes of the TREEADS models that will be implemented during the lifetime of the project.

The deliverable at hand has discussed and thoroughly analysed matters related to ecological modelling, as well as its extensions into environmental implications of wildfire effects. The modelling methodologies were considered for the prediction of fire weather, potential lighting events and fire occurrence, to draw conclusions in terms of effective fire management and mitigation, through means of effective planning and policy-making for the minimisation of wildfire preparedness overhead.

Additionally, the implications of societal and economic factors and relevant models as metrics for the prediction and prevention of wildfires were considered. Continuing, an analysis of restoration and adaptation models was conducted. More specifically, a discussion and documentation were implemented of the implications of climate change, and the overall role it plays in wildfire occurrence frequency but also severity. Consequently, the effects of soil erosion and its direct correlation with climate change were considered and in turn its own effects on a locale. It is noteworthy, that climate change, soil erosion and natural catastrophes are directly tied into a perpetually cascading feedback-loop, further amplifying the severely negative effects of wildfires on delicate ecospheres and landscapes. Smoke propagation and particulate levels and in turn analysed as direct consequences of wildfires, with its own effects having long-term environmental consequences. As expected, the overall conditions of affected ecosystems are directly correlated with the type(s), density and water content of local flora, and its capacity to constitute wildfire fuel. It must be highlighted that wildfires effects' severity in terms of soil erosion is also tied to the duration and rate of spread of the fire.

Concluding, D3.1 provided a first high-level description of the wildfire models used and/or developed within the TREEADS project. Each responsible partner engaged in a descriptive analysis of all the wildfire models proposed so far, which is contributed by all the corresponding TREEADS partners. Additionally, information regarding the respective wildfire modelling scopes and goals, namely prevention, preparedness, detection, response, restoration, and adaptation is provided and mapped into fire modelling typologies such as empirical, semi-empirical and physical. All provided input data and types are mapped to desired outcomes of the respective wildfire model, along with potentially related standards, requirements and the pilots use cases of TREEADS.

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TREEADS

A Holistic Fire Management Ecosystem for Prevention, Detection and Restoration of Environmental Disasters

The Members of the TREEADS Consortium:

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