



# **A** Systematic Review of Applications of Machine Learning Techniques for Wildfire Management Decision Support

Karol Bot \* and José G. Borges D

Forest Research Center and Laboratory Terra, School of Agriculture, University of Lisbon, Tapada da Ajuda, 1349-017 Lisboa, Portugal; joseborges@isa.ulisboa.pt

\* Correspondence: karolbot@isa.ulisboa.pt

Abstract: Wildfires threaten and kill people, destroy urban and rural property, degrade air quality, ravage forest ecosystems, and contribute to global warming. Wildfire management decision support models are thus important for avoiding or mitigating the effects of these events. In this context, this paper aims at providing a review of recent applications of machine learning methods for wildfire management decision support. The emphasis is on providing a summary of these applications with a classification according to the case study type, machine learning method, case study location, and performance metrics. The review considers documents published in the last four years, using a sample of 135 documents (review articles and research articles). It is concluded that the adoption of machine learning methods may contribute to enhancing support in different fire management phases.

Keywords: wildfires; machine learning; applications; decision support; review



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# 1. Introduction

Wildfires, e.g., uncontrolled fires occurring in forest or grassland in rural areas [1], threaten and kill people, destroy urban and rural property, degrade air quality, ravage forest ecosystems and Natura 2000 sites, and contribute to global warming. The connection between climate change and the increased risk of wildfires suggests a paradigm change in the co-existence of humans with natural catastrophes affecting the environment [2]. Indeed, the regime of wildfires in the Anthropocene is changing due to this complex fire–human–climate interaction [3]. The forest fires paradox has been highlighted by several authors [4–6]. They may play an important ecological role by removing deadwood and opening space for the growth of new vegetation. They may also release nutrients into the soil and offer ecological niches for the proliferation of wildlife. In contrast, when occurring at high intensity, forest fires lead to negative environmental impacts such as a decrease in soil quality (e.g., loss of biota, volatilization of its nutrients, and an increase in erosion). They may further contribute to a decline in biodiversity, as well as to a decrease in air quality [3,4], thus threatening forested landscapes [7].

Wildfires result from the interaction of several factors (e.g., the composition of the fuels, ignition sources, weather conditions, and topography) [8]. The landscape mosaic impacts the wildfire development process, e.g., fire ignition and frequency, rate of spread, the energy released, and the severity [3]. The complexity of the phenomenon poses a challenge to its modelling and simulation in order to address wildfire hazards proactively, i.e., to enhance silvicultural practices and forest management plans to design resilient landscapes and to reduce loss [9–12] According to the EU Horizon 2020 Work Programme [11], the fire management cycle may be broadly segmented into three stages: (i) prevention and preparedness (pre-fire); (ii) detection and response (management of active wildfires); (iii) restoration and adaptation activities (post-wildfire). The literature discusses the research into methods and tools to help address each stage, as well as the policy emphasis on each [12,13].

The literature reports a variety of models targeting specific stages of the fire management cycle, e.g., wildfire occurrence models, wildfire damage models (e.g., [14–18]), wildfire spread models [9,12,19], fuel and stand growth and yield models, stand-level management scheduling methods, forested landscape management methods (e.g., [20,21]), dispatch and deployment models, and information and decision systems as technological support platforms (e.g., [15–17,22]). Scientific methods, namely, statistical modelling and operations research analysis have contributed greatly to understanding the behaviour and driving factors of wildfires, as well as providing situational awareness and decision support to improve operational decision-making [23,24]. Nevertheless, despite scientific and technological breakthroughs in addressing specific fire management problems, new approaches are needed to understand the complex wildfire phenomenon and mitigate its impacts [3]. The use of machine learning models is a well-established approach in many fields of science [20,21], and could thus be an option to address the challenges faced by wildfire management.

According to [25], "machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment". Furthermore, it "can improve automatically through experience" [8]. In [8], the most frequently used machine learning approaches are detailed from a wildfire perspective. The authors briefly present popular algorithms within each category (supervised, unsupervised, and agent-based), along with references that discuss the fundamentals of machine learning methods. Details considering the theory of supervised learning may be found in [26-28]. Supervised learning aims to map labelled input to known output, using a continuous target variable or a categorical target variable. The continuous target variable is used for regression tasks, with possible applications in this context in fire susceptibility, fire spread/burn area prediction, fire occurrence, fire severity, smoke prediction, and climate change assessment [8]. Some of the popular algorithms for regression tasks are: naive Bayes [29], decision trees [30], classification and regression trees [31], random forest [32], deep neural network [33], Gaussian processes [34], neural networks [35], genetic algorithms [36], recurrent neural networks [37], and maximum entropy [38]. The categorical target variable is used for classification tasks, with possible applications in this context in fuel characterization, fire detection and fire mapping, for example [8]. Popular algorithms for classification tasks are: neural networks, decision trees, boosted regression trees (gradient boosted machine) [39], random forest, K-nearest neighbour [40], and support vector machines [41]. Details on the theory of unsupervised learning may be found in [28]. Unsupervised learning aims to understand patterns and discover outputs, using data in which the target variable is not available. It can be used for clustering and dimensionality reduction tasks. Possible applications for the clustering task, in this scope, are fire detection, fire mapping, burned area prediction, and fire weather prediction [8]. Popular algorithms for clustering tasks are: K-means clustering [42], self-organizing maps [43], autoencoders, Gaussian mixture models [44], ISODATA, hidden Markov models [45], and hard competitive learning [46]. Possible applications for the dimensionality reduction task are landscape controls on fire, fire susceptibility, and fire spread/burned area prediction [8]. Popular algorithms for dimensionality reduction tasks are: self-organizing maps, autoencoders, t-distributed stochastic neighbour embedding [47], random forest, boosted regression trees (also known as gradient boosted machine), and maximum entropy.

Nevertheless, as highlighted by the literature, innovations in wildfire management decision support have consisted mostly of advancements in the field of operational research approaches. There is little experience of taking advantage of the potential of machine learning or deep reinforcement learning techniques—as briefly outlined above—to enhance wildfire management decision support (e.g., [3,48]). This provided the motivation for a review of machine learning techniques and applications that may provide insights into their potential to address the complexity of a holistic approach to fire management. This review considers recent (2019–present) applications of machine learning methods for wildfire management decision support, considering the last four years of publications. The

emphasis is on providing a summary and a classification of the applications according to the study type, main application of the model, machine learning technique, case study location, and performance metrics.

## Objective, Contribution, and Organization of the Work

The present work aims at developing a review of the recent applications of machine learning methods for wildfire management decision support, considering the last four years of publications (from 2019 to the present). This review aims at providing the following contributions:

- A summary of the applications developed by the studies mentioned;
- A classification according to the study type, main application of the model, machine learning technique, case study location, and performance metrics.

The work is organized into four main sections. Section 1 provides an introduction to the scope of the work and its objectives and contributions. Section 2 presents the methodology used for the development of the systematic review. Section 3 presents references to the basics of wildfire modelling and machine learning methods, fundamentally presenting the review results. Section 4 presents the conclusions.

#### 2. Systematic Review Methodology

2.1. Database and Search Terms

The review was built from the Clarivate Web of Science database. The search terms were ("machine learning" OR "computational learning") AND ("wildfire" OR "fire").

## 2.2. Eligibility Criteria

The criteria for selecting results from the database queries were: (i) a time interval of four years (from 2019 to the present); (ii) the document type being a journal research article or review article; (iii) a pertinent match of the title and abstract to the objective of this work (a focus on wildfire modelling using machine learning techniques); (iv) detailed consideration of the whole document to assess its relevance (description of the machine learning technique used, description of the wildfire modelling application, description of the input data and main results).

## 2.3. Data Collection Results

Figure 1 presents the results (in numeric terms) for each filtering stage in the systematic review methodology. The initial search comprised 682 documents, and the final stage (where the documents were considered eligible and are included in this review) comprised 135 documents.



Figure 1. Schematic of search method and obtained results for each document filtering stage.

# 3. Results

The results highlighted four earlier reviews of applications of machine learning methods to wildfire management. In Section 3.1, we list these reviews and highlight further the motivation for this new review and its added value. Subsequently, we present a summary of all papers with an emphasis on the methods and techniques used (Section 3.2). The methods' input features and feature selection are further explored in Section 3.3. Finally, Section 3.4 discusses the research trends, challenges, and prospects regarding the applications of machine-learning-based methods to wildfire management.

#### 3.1. Related Reviews

Three review papers were identified within the final sample of 135 studies focusing on machine learning applications in wildfire management decision support (Table 1). In contrast with these reviews, the present work classifies the documents according to the wildfire management decision support stage, namely, (i) prevention and other related prefire decision support applications, (ii) active wildfire-related decision support applications, and (iii) restoration and other post-fire-related decision support applications. Moreover, this review has a broader scope and updates the findings from earlier reviews, as highlighted in the following sub-sections.

Ref. Title Addressed Issues Overview of popular machine learning methods, A review of machine learning [8] applications in wildfire science and review of applications and advantages and limitations of the methods management Review methods based on geospatial Forest fire induced Natech risk information systems (GIS) for modelling wildfire [49] assessment: A survey of geospatial risk and their Natural Hazards Triggering technologies Technological Disasters (Natech) potential A Survey of Machine Learning Review of various methods used in forest fires [50] Algorithms Based Forest Fires prediction and detection Prediction and Detection Systems

Table 1. Results: pertinent review articles and addressed issues.

#### 3.2. Machine-Learning-Based Applications

The applications are classified into three main categories: pre-fire prevention, active wildfire, and restoration and post-fire. We outline the application, machine learning technique employed, case study location, and model performance metrics in Tables 2–4, for the documents in which there is comprehensive description of the machine learning method employed. This outline is intended to support the discussion of results and facilitate further reference in the case of applications where the machine learning method is fully described.

## 3.2.1. Pre-Fire Prevention and Preparedness

The 51 papers addressing this wildfire cycle management phase focused on the following applications: wildfire fuel modelling, risk assessment and ignition prediction of wildfires, support to dispatch, landscape planning and prevention measures for severity mitigation, and development of inventory data. Of the 51 articles, 13.7% applied machine learning to wildfire fuel modelling (A), 78.4% to risk assessment and ignition prediction of wildfires (B), nearly 2.0% to landscape planning and prevention measures for severity mitigation (D), and 5.9% to the development of inventory data (E).

# Wildfire Fuel Modelling

In [51], The improvement of the monitoring of Fuel Management Zones has been studied using extreme gradient boosting, support vector machine, random forest, and K-nearest neighbours machine learning methods, fed with data from satellite images, vege-

tation indices and temporal characteristics. In [52], the authors generated initial boundary conditions for coupled fire–atmosphere simulations that assessed the fuel representation, using imagery, machine learning, and field sampling. In [53], high-resolution fuel moisture content and gridded data are developed, with the aim of assimilation into operational fire prediction (by establishing relationships between the satellite reflectance, surface weather and soil moisture observations, and fuel moisture content). Surface observations were used to train multiple machine learning methods (multiple linear regression, random forests (RFs), gradient boosted regression, and neural networks).

In [54], the authors combined multi-source remote sensing and field data with machine learning techniques (random forest and support vector machine) and traditional regression models, to estimate the dead fuel load in a 1 h time horizon, and to understand its determining factors. In [55], the authors developed models to estimate the fuel moisture content in a 10 h horizon, making use within their framework of random forest and support vector machine methods.

A mask region-based convolutional neural network approach was used to automate dead tree detection from aerial spaces in [56]. In [57], neural networks are used to classify the presence of wildfire-ignitable liquids on the ground. In [58], a similar approach is adopted, but instead using K-nearest neighbours and support vector machine.

The optimal timing and location of fuel treatments and timber harvesting to prevent wildfires is studied in [59], where the authors use approximate dynamic programming and account for the spatial interactions that generate fire risk.

#### Risk Assessment and Ignition Prediction of Wildfires

These applications assess both the likelihood of wildfire occurrence and the occurrence impacts [60], and are an important component of disaster and risk mitigation studies [61]. In [2], the authors used random undersampling and boosting to address the drivers of a wildfire occurrence and to determine its risk from the multidimensional perspective of human activity, topology and geography, and land coverage, to deliver findings that can be used for territorial planning. In [62], remote sensing and machine learning techniques were used to explore fire determinant features (topography and human-accessibility-related features) and also to predict the probability of fire occurrence and danger. Fire danger maps are studied in [63], but from an approach of evaluation of a land cover map and information from previous fire-affected areas, among other features.

In [64], the wildfire risk is analysed under climate change scenarios, by developing fire frequency predictions employing random forest, support vector machine and polynomial machine learning regression methods. In [65], maximum entropy and random forest methods were tested to determine the risk of wildfire based on satellite images at various spatial and spectral resolutions.

A forest fire susceptibility index and a social/infrastructural vulnerability index are developed in [66], employing machine learning methods and GIS multi-criteria decision-making, with a forest fire susceptibility map as an output. In [67], the authors define a long-term index for wildfire risk and wildfire danger assessment by employing a fuzzy K-nearest neighbours classification approach. In [68], logistic regression, deep neural network, and fire risk indexing models are used to develop an optimized risk indexing system for wildfire risk assessment. Anthropogenic features were also assessed in [69] via the application of machine learning models to predict forest fires. In [70], an hourly risk index is developed based on a CatBoost method. In [71], socio-economic factors are also considered to determine the wildfire probability using a maximum entropy method associated with a random forest method.

In [72], forest susceptibility risk is explored using a new ensemble model based on two deep neural networks, and the model is compared with methods such as extreme gradient boosting and support vector machine. Another susceptibility map is elaborated in [73], based on a random forest method that takes into consideration previous fire perimeters and various geo-environmental predisposing factors. In [74], forest fire susceptibility

mapping was developed by employing a LogitBoost ensemble-based decision tree method and benchmarked against support vector machine, random forest, and kernel logistic regression. In [75], geospatial data, multiple machine learning (neural networks, support vector machine, and maximum entropy, among others), and spatial statistical tools are used to demarcate the susceptibility to fire in forests using a weighted approach. In [76], a machine learning ensemble approach (based on the prediction results of support vector machine and random forest) is developed to predict wildfires. In [77], the susceptibility assessment is performed via the random forest method.

In [78], the performance of many machine learning algorithms (naive Bayes, Bayes network, multivariate logistic regression, and decision tree) are tested for the prediction and development of a fire susceptibility map. The performance accuracy is also evaluated in [79], in which boosted regression tree, functional discriminant analysis, classification and regression trees, generalized linear model, random forest, mixture discriminant analysis, and a few hybrid methods are developed to predict wildfire hazard and wildfire-prone areas. In addition, in [80], a multi-hazard risk map (in which wildfires are included) is developed, and the approach (using support vector machine, boosted regression tree, and generalized linear model methods) focuses on the improvement of its accuracy. The improvement of fire risk mapping via satellite-derived metrics is studied in [81], in which logistic regression, random forest, and extreme gradient boosting are used. Forest susceptibility is mapped by new hybrid algorithms proposed in [82], and in [83] that susceptibility is assessed by employing a local weighted learning algorithm with cascade generalization. Forest hazards are also evaluated in [84], by employing an optimized repeatedly random undersampling method using support vector machine and a genetic algorithm to compute its parameters.

In [85], the wildfire occurrence is predicted by employing random forest algorithms and cluster analysis. The authors analyse changes in spatial patterns of ignition probability over time, taking into consideration human-related drivers, among others. In [86], the estimation of wildfire probability is achieved by employing neural networks and taking into consideration features related to biophysical and human drivers.

In [87], a combination of big data, remote sensing, and machine learning methods (neural networks and support vector machine) is used to extract insights from satellite images to model the prediction of the occurrence of wildfires. In [88], the authors use machine learning methods to assess the probability of a fire event starting within a 24 h horizon from lightning events. In [3], the authors use a deep neural network approach to estimate and predict wildfire ignition risk, mainly based on topological attributes. In [4], a GIS-aided maximum entropy method is used for the development of a fire prediction map, and a feature selection study is performed considering environmental features. In [89], a total of thirty-six features are evaluated to determine those that provide better performance of the prediction model. In [1], the authors used random forest models and an ensemble approach to predict wildfire risk. A convolutional neural network is used to deliver a spatial prediction model for forest fires in [90], using a set of GIS-based data. In [91], a GIS-based machine learning method is also developed, in which multiple machine learning methods are tested.

In [92], the authors employ a broad diversity of machine learning methods targeting the prediction of the occurrence of forest fires (namely, decision forest classifier, boosted decision trees, decision jungle classifier, averaged perceptron, local deep support vector machine, 2-class Bayes point machine, logistic regression, and binary neural network). Based on the comparison of results, the authors proposed an Internet-of-Things-based smart fire prediction system. In [93], detailed topological features are used in a hybrid artificial intelligence model (composed of multivariate adaptive regression splines optimized by differential flower pollination). In [94], the authors develop a comparison between the prediction of fire behaviour using machine learning and a physically based method, mainly evaluating the performance and computational time. The focus is on the calibration of wildfire prediction machine learning models in [60], in which the methods of random forests, neural networks, and classification trees are the objects of study, in comparison with

traditional methods such as logistic regression and logistic generalized additive models. Random forest is also used in [95].

In [96], the probability of wildfire is modelled based on a machine learning approach, and it is analysed in terms of the costs associated with the implementation of multiple prescriptions for risk mitigation. In [97], the authors assess, by means of employing gradient boosting tree, the impact of weather on the damage caused by fire incidents and also predict its risk. In [98], a model is proposed to predict fire risk one month in advance.

#### Support to Dispatch

The work presented in [99] aims at supporting wildfire planning management activities by establishing road interrelations between wildfire operational delineations and potential control locations, using boosted regression models to facilitate future dispatch of suppression resources. In [100], work is also focused on the firefighters dispatch strategy, by assessing the probability of fire containment. The models used as training data georeferenced historical fire data concerning ignition locations, previous responses, and weather conditions. They assessed different gradients of features such as detection time, ground accessibility, and aerial support.

## Landscape Planning and Prevention Measures for Severity Mitigation

In [48], the authors assess the delineation of the wildland–urban interface based on wildfire risk assessment, with a focus on whether fire-based machine learning mapping enhances the spatial congruence of houses and wildfires, compared with conventional methods. In [101], the authors study the landslide and wildfire intersection susceptibility, taking into consideration the uncertainty of susceptibility maps by using three advanced ensemble machine learning algorithms: adaptive boosting, random forest and gradient boosting decision tree. In [102], four machine learning classifiers were applied to establish the wildland–urban interface definition based on fire occurrence data, focusing on housing density and vegetation coverage. Finally, in [103], the impacts of prescribed burning treatments are assessed using the random forest method, with the aim of reducing extreme wildfires. Eight features were evaluated, among them the fire return interval, the seasonality of the burn, and hydrological and climatic variables.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Machine Learning Case Study Technique Location	
[51]	А	Methods of Fuel Management Zone improvement	Extreme Gradient Boosting, Support Vector Machines, K-Nearest Neighbours, and Random Forest.		F1-score ranging from 90.0% up to 94.0% and a Kappa ranging from 0.80 up to 0.89.
[53]	А	Determining fuel moisture content	Multiple Linear Regression, Random Forests, Gradient Boosted Regression, and Neural Networks	United States	Errors between 25.0–33.0%
[54]	А	Estimating fine dead fuel load and understand its determining factors	Multiple Linear Regression, Random Forest, and Support Vector Machine		Random Forest: RMSE: 0.09; MSE: 0.01; r: 0.71; R-2: 0.50)
[55]	А	Estimating 10 h fuel moisture content	Random Forest and Support Vector Machine	m Forest and Support Vector Machine	

#### Table 2. Results: pre-fire prevention applications.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[56]	А	Detection of dead trees from aerial images	Mask Region-Based Convolutional Neural Network		Mean average precision score = 54.0%
[57]	А	Detection of ignitable liquids on ground-truth fire debris	Neural Networks		False positive rate of 0.07 and a true positive rate of 0.59
[58]	А	Detection of ignitable liquid residue on fire debris	Linear and Quadratic Discriminant Analysis, K-Nearest Neighbours, and Support Vector Machines with Radial and Linear Kernels	near and Quadratic scriminant Analysis, arest Neighbours, and port Vector Machines h Radial and Linear Kernels	
[60]	В	Methods for properly calibrating statistical and machine learning models for fine-scale, spatially explicit daily fire occurrence prediction	Classification Trees, Random Forests, Neural Networks, Logistic Regression Models, and Logistic Generalized Additive Models	Alberta, Canada	
[61]	В	Monitoring fire risks over a large region	Transductive PU Learning	Southeast China	High sensitivity (>80.0%)
[2]	В	Addressing the multidimensional effects of three groups of drivers in territorial planning under fire risk	Random Undersampling and Boosting	Chile	Area under the receiver operating characteristic curve of 0.967 and an overall accuracy over test data of 93.0%
[63]	В	Modelling fire danger	Support Vector Machine, Generalized Linear Model, Functional Data Analysis, and Random Forest	Iran	Area under the receiver operating characteristic curve of 0.855
[64]	В	Analysing the influences of climate warming on fire risk	Random Forest, Support Vector Machine and Polynomial	Changsha, China	
[65]	В	Determining the risk of fire	Maxent and Random Forest	Yakutia, Russia	
[66]	В	Developing spatial prediction of wildfire susceptibility	Artificial Neural Network, Support Vector Machines, and Random Forest	Iran	Accuracies between 74.0–88.0%
[67]	В	Defining a long-term wildfire warning index	Fuzzy K-Nearest Neighbours	Brazil	
[68]	В	Optimizing risk indexing for fire risk assessment	Deep Neural Networks	Korea	
[69]	В	Determining the main explanatory variables for forest fire occurrence and mapping of probability	Random Forest	Eastern Serbia	

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[70]	В	Developing an hourly forest fire risk index	CatBoost	South Korea	Area under the receiver operating characteristic curve = 0.8434
[71]	В	Estimating and analysing how human activity is influencing forest fire probability	Maximum Entropy (Maxent) and Random Forest	South Korea	
[72]	В	Prediction of fire susceptibility and effects of sample patch sizes on the predictive performance of the algorithms	Deep Neural Network	Chile	Area under the curve = 0.953
[73]	В	Elaborating a wildfire susceptibility map	Random Forests	Italy	
[74]	В	Developing a forest fire susceptibility map	LogitBoost Ensemble-Based Decision Tree	Vietnam	92.0% prediction capability
[75]	В	Weighted approach to characterizing the forest fire susceptibility	Artificial Neural Network, Generalized Linear Model, Multivariate Adaptive Regression Splines, Naive Bayesian Classifier, K-Nearest Neighbour, Support Vector Machine, Random Forest, Gradient Boosting Machine, Adaptive Boosting, and Maximum Entropy (Maxent)	Kerala, India	Receiver operating characteristics—area under curve values ranging from 0.869 to 0.924
[76]	В	Generating susceptibility maps of forest fires	Support Vector Machine, Random Forest, and Ensemble	Serbia	Ensemble model had an area under curve = 0.848
[77]	В	Developing a model, in which probabilistic outputs allowed elaboration of wildfire susceptibility maps.	Random Forest	Bolivia	
[78]	В	Prediction and mapping of fire susceptibility	Bayes Network, Naive Bayes, Decision Tree, and Multivariate Logistic Regression	Pu Mat National Park, Nghe An Province, Vietnam	Area under curve = 0.96
[79]	В	Predicting the fire hazard in a fire-prone area	Boosted Regression Tree, Classification and Regression Trees, Functional Discriminant Analysis, Generalized Linear Model, Mixture Discriminant Analysis, Random Forest	Northeast Iran, Golestan Province.	Area under curve = 0.855
[80]	В	Producing an accurate multi-hazard risk map for a mountainous area	Support Vector Machine, Boosted Regression Tree, and Generalized Linear Model	Mountainous region of Iran	

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[81]	В	Investigating the impact of satellite-derived metrics that represent long-term vegetation status and dynamics on fire risk mapping	Logistic Regression, Random Forest, and Extreme Gradient Boosting	Mediterranean woodlands and forests	
[82]	В	Mapping forest fire susceptibility	Frequency Ratio–Multilayer Perceptron, Frequency Ratio—Logistic Regression, Frequency Ratio–Classification and Regression Tree, Frequency Ratio–Support Vector Machine, and Frequency Ratio–Random Forest	North Morocco	Area under curve = 0.989
[83]	В	Prediction of forest fire susceptibility	Locally Weighted Learning Algorithm with the Cascade Generalization, Bagging, Decorate, and Dagging Ensemble Learning	Vietnam	Area under curve = 0.993
[84]	В	Computing the probability of hazard occurrence	Support Vector Machine and Genetic Algorithm		
[85]	В	Predicting and detecting changes in the spatial pattern of ignition probability over time.	Random Forest	Brazil	Area under curve = 0.72
[86]	В	Estimating wildfire probability occurrence as a function of biophysical and human-related drivers	Artificial Neural Network	Artificial Neural Network Alpine and subalpine region	
[87]	В	Predicting the occurrence of wildfires	Artificial Neural Network and Support Vector Machine		Prediction accuracy = 98.3%
[3]	В	Estimating and predicting wildfire ignition risk	Deep Neural Network		
[4]	В	Proposing forest fire prediction map	Maximum Entropy	Brazil and Australia	Area under curve = 0.95
[1]	В	Predicting the wildfire risk	Random Forest	Monticello and Winters, California	Accuracy of 92.0%
[90]	В	Proposing a spatial prediction model for forest fire susceptibility	Convolutional Neural Network	Yunnan Province, China	Area under curve = 0.86
[91]	В	Assessing forest fire susceptibility	Boosted Regression Tree, General Linear Model, and Mixture Discriminant Analysis	Fars Province, Iran	

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[92]	В	Predicting occurrence of forest fires	Boosted Decision Trees, Decision Forest Classifier, Decision Jungle Classifier, Averaged Perceptron, 2-Class Bayes Point Machine, Local Deep Support Vector Machine, Logistic Regression, and Binary Neural Network		Area under the curve = 0.78
[93]	В	Analysing and predicting spatial patterns of forest fire danger	Multivariate Adaptive Regression Splines Optimized by Differential Flower Pollination	Lao Cai province (Vietnam)	Area under the curve = 0.91
[94]	В	Providing details on specific techniques being explored for performing low-cost, high fidelity fire predictions	Deep Neural Networks		
[60]	В	Developing methods for properly calibrating statistical and machine learning models for fine-scale, spatially explicit daily predictions	Classification Trees, Random Forests, Neural Networks, Logistic Regression Models, and Logistic Generalized Additive Models	Lac La Biche region of Alberta, Canada	
[95]	В	Estimating the probability of fire occurrence	Random Forest	Colombian– Venezuelan plains (llanos) ecoregion in South America.	Accuracy of 94.0%
[97]	В	Studying the impact of weather on the damage caused by fire incidents	Gradient Boosting Tree	United States	R-2 value of 0.933 and mean squared error (MSE) of 124.641 out of 10,000
[98]	В	Prediction of African fire one month in advance and generalizing to provide seasonal estimates of regional and global fire risk	Stepwise Generalized Equilibrium Feedback Assessment	Africa	
[101]	D	Developing susceptibility maps considering the intersection of landslide and wildfire susceptibility and the spatial uncertainty	Random Forest, Gradient Boosting Decision Tree, and Adaptive Boosting		

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[104]	Е	Creating wildfire inventory data by integrating the polygons collected through field surveys using global positioning systems (GPS) and the data collected from the moderate resolution imaging spectrometer (MODIS) thermal anomalies product	Artificial Neural Network, Dmine Regression, DM Neural, Least Angle Regression, Multi-Layer Perceptron, Random Forest, Radial Basis Function, Self-Organizing Maps, Support Vector Machine, and Decision Tree		
[105]	Е	Developing an automatized and cloud-based workflow for generating a training dataset of fire events at a continental level using freely available remote sensing data	Random Forest, Naive Bayes, and Classification and Regression Tree.		
[106]	Е	Creating a wildfire data inventory by integrating global positioning system (GPS) polygons with data collected from the moderate resolution imaging spectroradiometer (MODIS) thermal anomalies product	Artificial Neural Network, Support Vector Machines, and Random Forest	Amol County, northern Iran.	

<sup>1</sup> References were classified according to the application focus: (A) wildfire fuel modelling; (B) risk assessment and ignition prediction of wildfires; (D) landscape planning and prevention measures for severity mitigation; (E) development of inventory data.

## Development of Inventory Data

In [104], the wildfire susceptibility was assessed and inventory data were developed by the integration of GPS and MODIS thermal anomalies product data. Along with the developed inventory data, conditioning factors were selected and tested with ten different machine learning methods and compared against the traditional logistic regression method. In [105], the authors create inventory data for training machine learning models of fire events using freely available remote sensing data. The training dataset generated was applied in random forest, classification and regression tree, and naïve Bayes methods. In [106], a wildfire and conditioning factors data inventory is proposed by also integrating GPS and MODIS data. The authors demonstrate the application of neural networks, support vector machine, and random forest to the data.

Table 2 presents in more details the classification of the mentioned articles considering the pre-fire prevention applications.

## 3.2.2. Management of Active Wildfires (Detection and Response)

The 21 papers addressing this wildfire cycle management phase focused on the following applications: wildfire detection, wildfire spread prediction, and wildfire suppression. Of the 21 articles, 61.9% applied machine learning to wildfire detection (A), 23.8% to wildfire spread prediction (B), and 14.3% to wildfire suppression (C).

#### Wildfire Detection

The ability to rapidly detect the ignition of a wildfire is of paramount importance in order to avoid the wildfire turning into an extreme wildfire event [107]. There is thus an urgent need to focus on high-performance forest fire detection models. Wildfire detection models should ideally have high fire detection rate and a low false alarm rate [108].

A machine learning image-based model prototype was developed in [109], to detect smoke from fires within 15 min of ignition. In [110], an image-based smoke detection method is designed, based on a convolutional neural network approach that works as a binary classifier. In [111], an imagery-based detection model is presented, and a decision rule and a Gaussian mixture model are employed to train the model. The authors in [112] also use imagery-based fire detection, associated with the random forest method to reduce false alarms. In [113], image features are used alongside a long short term memory network and a convolutional neural network. Deep learning is used in a multi-level forest detection method for wildfires in [114]. In [115], an adaptive quasi-unsupervised approach is used to monitor the boundary conditions to detect forest fires.

A multi-sensor machine-learning-based system is developed in [116], based also on neural networks. In [117], a similar approach is used but the focus is on surveillance camera use. A fire-flake generator model based on ambient features and machine learning is developed in [118]. In [119], PRISMA sensor data were associated with classification techniques from the support vector machine method.

In [108], the authors aim to increase the accuracy of detection and reduce false alarms by using a K-nearest neighbour method. In [120], powerlines are used associated with extreme gradient boosting machine learning to detect wildfires. In [61], the authors used transductive learning from the positive and unlabelled (PU learning) data method to identify forest fire occurrence, strongly based on remote sensing data. In [121], satellite images are used to identify forest fires, based on a random forest method.

#### Wildfire Spread Prediction

In [122], an in-time methodology is developed both to optimize effective fire containment resource utilization and (mainly) to predict fire spread, through the use of an ensemble model based on machine learning methods (e.g., particle swarm and a bat algorithm), a heuristic approach and principal component regression. Short-term spread prediction is developed in [19], with real-time rate-of-spread measurements associated with a machine learning algorithm for correlation. In [123], the fire arrival time is estimated based on satellite data and the support vector machine.

In [124], the fire front spread is estimated using a deep convolutional inverse graphics network. In [125], the prediction of wildfire spread is evaluated by employing a statistical downscaling scheme based on deep learning associated with multi-source remote sensing data. In [126], the drivers for the fire spread predicted severity as well as prescriptions are evaluated, associating a random forest method with remote sensing data. In [127], biophysical and management drivers of the final estimated severity of spread are evaluated through the use of the random forest method. Final fire size is predicted at the time of ignition in [128], using decision trees. In [129], machine learning algorithms are integrated with multistage fire spread models. In [107], there is a special focus on developing inventory data to characterize the possibility of a wildfire becoming an extreme wildfire event. The results are applied to train four machine learning methods. The authors concluded that the use of data registered at the time of the wildfire contributes to increasing the accuracy in predicting the probability of a wildfire becoming an extreme wildfire event, compared to the use of historical data.

# Wildfire Suppression

In [130], the authors develop a digital twin framework that combines the track of the trajectory of released airborne materials for fire suppression and machine learning to optimize the release dynamics of the aircraft in a fast manner. In [131], the research assesses a sound-wave fire-extinguishing system, by means of applying machine learning methods (neural networks, deep neural networks, random forest, K-nearest neighbour, and ensemble methods) to the dataset, to also classify extinction and non-extinction states of the fire.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[110]	А	Proposing a two-module video smoke detection framework designed for embedded applications on local cameras	Lightweight Deep Convolutional Neural Network		
[111]	А	Proposing an intelligent fire detection method by investigating three approaches to detect fire based on three different colour models	Decision Rule and Gaussian Mixture Model		
[112]	А	Proposing a combined 3-step forest fire detection algorithm (i.e., thresholding, machine-learning-based modelling, and post-processing)	Random Forest	South Korea	Overall accuracy similar to 99.2%, probability of detection
[113]	А	Proposing a multistage fire detection method	Convolutional Neural Networks and Long Short Term Memory Networks		
[114]	А	Proposing a multi-level forest fire detection method	General Advanced Networks, Adaptive Boosting, Convolutional Neural Networks, and Support Vector Machine		
[116]	А	Proposing a method using machine learning techniques for multimedia surveillance during fire emergencies	Adaptive Boosting and Many Multi-Layer Perceptron Neural Networks		
[117]	А	Proposing a fire detection method using sensors and image data	Adaptive Boosting, Multi-Layer Perceptron Neural Networks, and Convolutional Neural Networks		
[118]	A	Proposing a data-driven fire-flake simulation model	Neural Network		
[119]	А	Exploring the potential use of the PRISMA sensor for active wildfire characterization	Support Vector Machine	New South Wales	

# Table 3. Results: management of active wildfire applications.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[108]	А	Proposing a method that widens the view of fire detection from conventional two-class to multi-class classification problems to meet complex forest image background	K-Nearest Neighbour Decision Tree		
[120]	А	Exploring and discovering the numerical patterns from the contact to the ignition process between different upper-storey vegetations and the powerlines	Hybrid Step Extreme Gradient Boosting		
[61]	А	Developing a workflow process to monitor fires over a large region	Transductive PU Learning	Southeast China	
[121]	А	Systematically testing and comparing reflectance and fractional cover candidate severity indices	Random Forest		
[123]	В	Estimating the fire arrival time from satellite data	Support Vector Machine	California, United States	12.0% burned area absolute percentage error; 5.0% total burned area mean percentage error, a 0.21 false alarm ratio average, a 0.86 probability of detection average, and a 0.82 Sorensen's coefficient average
[124]	В	Estimating the time-resolved spatial evolution of a wildland fire front	Deep Convolutional Inverse Graphics Network		
[125]	В	Developing a fire progression model considering the uncertainties	U-Net Convolutional Neural Network		
[126]	В	Identifying the main environmental factors driving fire severity in extreme fire events	Random Forest	California, USA	
[128]	В	Investigating the controls and predictability of final fire size at the time of ignition	Decision Tree		50.4 +/- 5.2% accuracy
[131]	С	Creating a sound-wave fire-extinguishing system and performing firefighting tests	Artificial Neural Network, K-Nearest Neighbour, Random Forest, Stacking, and Deep Neural Network Methods		

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case Study Location	Model Performance Metrics Results
[132]	С	Developing a sound-wave flame extinction system in order to extinguish the flames at an early stage of the fire	Adaptive-Network- Based Fuzzy Inference Systems), CN2 Rule and DT (Decision Tree)		
[133]	С	Creating an automated system that is capable of real-time, intelligent object detection and recognition and facilitating the improved situational awareness of firefighters during an emergency response	Convolutional Neural Network		

<sup>1</sup> References were classified according to the application focus: (A) wildfire detection; (B) wildfire spread prediction; (C) wildfire suppression.

In [132], the authors develop further a sound-wave flame extinction system to target the wildfire at a very early stage. It is based on a developed dataset that considers features such as fuel type, flame size, decibels, frequency, airflow, and distance. The approach employs adaptive-network-based fuzzy inference systems and decision tree methods. In [133], the authors propose an automated real-time system of intelligent object detection and recognition to improve the situational awareness of firefighters during wildfire emergency response, using convolutional neural networks to classify and identify objects of interest from thermal imagery.

Table 3 presents in more details the classification of the mentioned articles considering the management of active wildfire applications.

## 3.2.3. Post-Fire Wildfires (Restoration and Adaptation Activities)

The evaluation of wildfire severity in a given area is of importance, as it allows us to estimate the economic impacts of the wildfire [134]. It further provides information to support restoration decisions and the prioritization of post-fire management strategies [135,136]. The 34 papers addressing this wildfire cycle management phase focused on the following applications: burned area and severity, impacts related to social factors, impacts related to carbon fluxes, and impacts related to forest conditions. Of the 34 articles, 61.8% applied machine learning to the characterization of burned area and severity (A), 8.8% to the assessment of impacts related to social factors (B), 5.9% to the assessment of impacts related to carbon fluxes (C), and 23.5% to the assessment of impacts related to forest conditions (D).

#### Burned Area and Severity

Socio-economic features are evaluated in [137] along with meteorological and land surface characteristics, and the Shapley additive explanation method is used to predict the burned area. In [138], the authors assess the degree to which the machine learning training data affect the classification accuracy of fire severity modelling prediction. They consider the sample size and sample imbalance, also assessing the transferability of models to different geographic regions. In [139], random forest machine learning was used to determine the influence of pre-fire vegetation structure, weather conditions, and fire history on the wildfire severity, and to deliver management recommendations to mitigate the damage. In [140], an ensemble of machine learning methods approach is employed to predict the burned area. In [134], prediction of the severity is achieved using a combination of classification and regression machine learning algorithms.

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In [141], the authors used machine learning methods to estimate the burned area after a wildfire based on environmental factors such as fuel moisture, precipitation, vapour pressure, and temporal scale (dataset size). In [142], four hybrid models are compared to map wildland fire effects, using support vector machine and an adaptive neuro-fuzzy influence system, as well as meta-heuristic models. In [143], one of the modelling stages encompasses the processing of thematic maps of the area burnt, using machine learning techniques. In [136], automatic mapping of burned areas is achieved through the use of deep learning, considering a variety of network architectures applied to satellite data. The authors in [144] used pre and post-fire satellite images to identify the burn severity, employing random forest and support vector machine supervised classification. In [145], random forest also is used. Satellite imagery is used in [146], coupled with a random forest algorithm, both to detect recently burned areas and also to estimate the fire history.

In [147], remote sensing and machine learning are used to characterize burned areas in order to generate a map. Burned area detection for large areas is explored in [148], by means of satellite imagery and machine learning methods. In [149], the burned area is detected by evaluating the canopy cover pre- and post-fire, according to classification performed via machine learning. In another study, [150], a mask region-based convolutional neural network was used, coupled with a support vector machine to determine the post-fire affected areas, including pixels under the trees, based on images of the tree crowns. In [151], this detection is achieved through the analysis of reflectance contrasts associated with a classification regression tree algorithm. In [152–154], satellite images and the random forest machine learning method were used for the same purpose. In [155], various machine learning methods are assessed to determine the best fit for burned area prediction. In [156], the study focuses on the use of unsupervised methods. In [157], spectral indices associated with burned areas are classified by a random forest algorithm. In [158], neural networks are used and the accuracy is evaluated. In [159], the authors use a random forest method to develop a model that assesses the relationship between the severity of the wildfire and the previous suite of environmental conditions.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case study Location	Model Performance Metrics Results
[137]	А	Incorporating predictors of local meteorology, land-surface characteristics, and socio-economic variables to predict monthly burned area	Shapley Additive Explanation	United States	
[138]	А	Examining how training data properties affect fire severity classification across forest, woodland, and shrubland communities		Southern Australia	
[139]	А	Determining the main environmental variables that control fire severity in large fires	Random Forest	Iberian Peninsula	
[140]	A	Predicting the burned area of forest fires and the occurrence of large-scale forest fires		Portugal	
[141]	A	Topological data analysis to assess the final burned area		United States	

Table 4. Results: post-wildfire and restoration.

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case study Location	Model Performance Metrics Results
[142]	А	Mapping wildland fires	Support Vector Regression and the Adaptive Neuro-Fuzzy Inference System	Jerash Province, Jordan	
[143]	А	Determining relationships existing between the triggering of landslides and burnt areas through processing of the thematic maps of the burnt areas and landslide susceptibility assessment			
[136]	А	Developing models for automatically mapping burned areas from unitemporal multispectral imagery			
[144]	А	Assessing burn severity across the burn scars and testing the effectiveness of several remote sensing methods for generating accurate map products	Random Forest and Support Vector Machine	Interior of Alaska	
[145]	А	Mapping of burned areas using microwave data	Random Forests		
[146]	А	Identifying burned areas and estimating the fire history	Random Forest	North Carolina, United States	
[147]	А	Using automatic algorithm approach to map burned areas from remote sensing			
[148]	А	Examining the use of sUAS imagery to train and validate burn severity and extent mapping of large wildland fires from various satellite images			
[149]	А	Calculating tree mortality through the comparison of hyperspatial post-fire canopy cover and pre-fire canopy cover	Mask Region-Based Convolutional Neural Network		
[150]	А	Determining trees and burned pixels in a post-fire forest	Mask Region-Based Convolutional Neural Network and Support Vector Machine		
[151]	А	Analysing bi-temporal (pre- and post-fire) reflectance contrast of burn-sensitive spectral bands	Classification Regression Tree, Random Forest, and Support Vector Machine		

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case study Location	Model Performance Metrics Results
[155]	А	Mapping burned and unburned areas, differentiating fire occurrence dates, and distinguishing between old and more recent fires	K-Nearest Neighbours Algorithm (K-NN), Support Vector Machine (SVM) And Random Forest	Mediterranean area	
[156]	А	Investigates the use capability of the free synthetic aperture radar data for burned area mapping		Portugal and Italy	
[157]	А	Test the applicability of a normalized difference spectral index with the shortwave infrared and blue spectral bands in accurately mapping burned areas	Random Forest		
[158]	А	Estimating burned areas in forest fires	Artificial Neural Network		
[159]	А	Examine the fine-scale association between burn severity and a suite of environmental drivers	Random Forest	California, United States	Accuracy of 79.0% in classifying categories of burn severity
[160]	В	Evaluate public health impacts of wildfire smoke	Ordinary Multi-Linear Regression Method, Generalized Boosting Method, and Random Forest	United States	
[161]	В	Prediction models for ground-level ozone during wildfires, evaluating the predictive accuracy		California, United States	
[162]	В	Explored different combinations of biophysical and social factors to characterize wildfire-affected areas	Classification Trees	Portugal	
[163]	С	The carbon flux of the woodland was monitored to simulate daily net ecosystem production, ecosystem respiration, and gross primary production			
[164]	С	Calculating emissions associated with forest fires in Mexico, based on different satellite observation products	Random Forest	Mexico and United States	

Ref.	Classification <sup>1</sup>	Detailed Application	Machine Learning Technique	Case study Location	Model Performance Metrics Results
[135]	D	Proposes a unitemporal simulation approach based on the generation of synthetic spectral databases from linear spectral mixing to classify wildfire severity	Random Forest	Spain	Accuracy between 90.0–95.0%
[165]	D	Prediction of post-fire tree mortality	Random Forest		Reduced the bias in comparison with logistic regression method
[166]	D	Focus on the post-fire debris flow hazards analysis	Decision Tree Algorithm		Sensitivity of 81.0% and specificity of 78.0%
[167]	D	Map forest disturbance after a wildfire	Multiple Linear Regression, Support Vector Machine, and Random Forest	Northeastern China	
[168]	D	Identify temporal trends in post-fire regeneration and influences of climate on post-fire regeneration, with focus on post-fire establishment, initial post-fire density and radial growth			
[169]	D	Assessed the contributions of land cover composition, climate, and topography on the spatial forest regeneration	Boosted Regression Trees	New Mexico, United States	
[170]	D	Evaluate the potential of a radiative transfer model inversion approach for estimating fractional vegetation cover after wildfire from satellite reflectance data at high spatial resolution	Gaussian Processes Regression	Mediterranean Basin	
[171]	D	Assessed whether passive restoration of old trees could overcome constraints in time	Random Forest	Colorado, United States	

<sup>1</sup> References were classified according to the application focus: (A) burned area and severity; (B) impacts related to social factors; (C) impacts related to carbon fluxes; (D) impacts related to forest conditions.

Impacts Related to Social Factors

In [160], machine learning methods were used (e.g., ordinary multi-linear regression method, a random forest, and a generalized boosting method) to assess the public health impacts of the smoke generated by the wildfire, while considering the transportation and dispersion of the particles. In [161], the authors used machine learning prediction methods to estimate the ground-level ozone during the wildfires. In [162], the impact of wildfires on biophysical and social factors was analysed using classification trees.

#### Impacts Related to Carbon Fluxes

In [163], the carbon fluxes (carbon source and carbon sink) related to carbon sequestration were assessed using a machine learning regression technique, by analysing pre- and post-wildfire data, to contribute to post-fire ecology-related decision-making. In [164], the authors develop an approach based on a random forest regression model for estimating emissions associated with wildfires, using satellite observations.

## Impacts Related to Forest Conditions

In [135], the authors used random forest to develop four severity category classifications, where the model can detect the impacts of the wildfire on forests by classifying them as unburned, partial canopy unburned, canopy scorched, or canopy consumed. In [165], the authors predict tree mortality by employing a random forest model, and also evaluate the bias related to the model, in comparison with logistic regression.

In [166], a decision tree model is developed for the inductive inference of categorical data characterization, aiming at the post-fire analysis of debris hazards. In [167], stepwise multiple linear regression, support vector machine, and random forest were employed to analyse the statistical relationships between the recovery of the post-fire vegetation and the factors influencing it. In [168], the authors used a combination of dendro-ecological methods and machine learning to focus on the post-fire forest generation, taking into consideration factors related to climate, topographic variation, and pre-fire structure. In [169], a boosted regression trees method is used to assess the contribution of factors such as cover composition, topography, and climate on the vegetation.

In [170], the authors study the impact of wildfires on top-of-canopy spectral reflectance, by means the of Gaussian processes regression method. The authors in [171] focused on a combination of GIS and random forest methods to assess the passive restoration of old trees over time.

Table 4 presents in more details the classification of the mentioned articles considering the post-wildfire and restoration applications.

#### 3.3. Machine-Learning-Based Model Features and Feature Selection Sensitivity Analysis

The use of high-dimensional data to train a model is a challenge in the application of machine learning. To address this, feature selection is used to remove irrelevant data or data with a lower impact on the model performance. The papers that explicitly presented a feature selection process aimed to select the best predictors by employing recursive feature elimination. In this framework, the size of the initial set of variables is recursively reduced, and an important related factor is attributed to each variable (as described in [88]), providing insights into which physical process associated with the variable with the biggest impact on the accuracy of the model. In order to contribute to the understanding the complex interrelationships between anthropogenic controls, wildfires, and the environment, while increasing the efficiency of decision-making support by removing unnecessary data, a feature selection process is developed in [3,61,62,64,99,110,117]. This is influential in reducing the computational time, improving the accuracy of the learning process, and facilitating the interpretation of the results [172].

#### 3.4. Identified Research Trends and Challenges

This review concluded that there is an obvious potential for adopting machine learning methods for forecasting and classification, in different stages of the wildfire management cycle.

First, we list the trends identified. The category of pre-fire prevention and preparedness was the one most addressed by the reviewed papers. Most machine learning applications in the pre-fire stage (Table 2) focused on the two broad categories of risk assessment and ignition prediction of wildfires (78.4%), followed by the use of machine learning for wildfire fuel modelling (13.7%). The remaining applications for this stage accounted for 7.9% of the studies. Most research focusing on the management of active wildfires reported the use of machine learning for wildfire detection (61.9%), followed by its use for wildfire spread prediction (23.8%), and wildfire suppression (14.3%).

In the post-wildfire stage, e.g., restoration and adaptation activities, machine learning approaches were mostly used for the assessment of burned areas severity (61.8%), followed by applications for the assessment of impacts related to post-fire forest conditions (23.5%), with the remaining applications accounting for 14.7% of the studies. A summary of research trends from the literature review includes:

- The increase in the use of ensemble modelling, which can reduce the inaccuracy and the computational time of the models by combining different models and machine learning techniques.
- The shifting focus from obtaining detailed physical interpretations to obtaining faster results based on input and output variables, especially at the stages in which the computational time of the modelling process is of critical importance, such as when dealing with active wildfires.
- The increasing concern with reducing the subjective bias associated with expertopinion-based methods, as well as with incorporating uncertainty analysis at the modelling or sub-modelling stages.
- The use in many papers of the association of remote sensing imageries, machine learning, and geospatial analysis to predict or classify variables of interest, in order to identify areas that are prone to wildfire occurrence.
- The exploration of classification and prediction using the main machine learning methods of random forest, support vector machine, and neural networks.
- The use, in many documents, of the association of multiple methods to obtain a more accurate set of candidate models for the same area, to provide a more refined sampling and to choose a final model, indicating that the researchers are exploring an integrated approach to benefit from the capabilities of different methods to assess the complex problem of wildfire modelling.

A variety of challenges still remain, associated with the use of machine learning methods to support wildfire management. Some of them are:

- The need for constant improvement, mainly to obtain faster models while enhancing the interpretability of the results. This is still a critical factor in machine-learning-based models.
- Overall, the studies did not present the computational time associated with the modelling process, which is necessary to evaluate the applicability of the models in such an important field as disaster management.
- Few studies developed feature selection to increase the efficiency of decision support.
- Lack of information about simulation platforms, precluding the comparison of the computational efficiency of different tools.
- Lack of experience of using global models that can be applied to different regions and with different datasets and thus of assessing the potential for generalization of the models via a parametric study of bias-variance trade-offs.
- Few studies are available that focus on the multifunctionality of forested landscape management planning, i.e., on integrating wildfire protection concerns in contexts characterized by demands for multiple ecosystem services.
- There is almost no analysis on the bare minimum amount of data needed for a useful model, especially for the active wildfire stage.
- Despite the fact that some methods deal with uncertainty, when models encompass
  forecasting the uncertainty may be substantial, thus impacting the results (as in the case
  of models that consider weather features) associated with management prescriptions.
- There are still few datasets for extensive wildfires, and most of the models are developed using smaller wildfire events for training, which may not correctly reflect the context of extreme wildfire events.

- The acquisition of landscape dynamics data usually requires migrating data between datasets to quantify spatial patterns and changes through space and time. More developments are still required in this field.
- There may be issues regarding model overfitting that still need to be addressed.
- There is a need to bridge the gaps between monitorization and learning, and the decision-making process.
- There is a need for broader models that can help integrate the different wildfire management stages.

## 4. Conclusions

This review contributed to the characterization of the state of the art on the application of machine learning techniques to wildfire management decision support. It provided a summary of 135 recent papers (published between 2019 and 2022) that used machine learning approaches to address wildfire management issues. It also provided a classification of these approaches according to the area of application, machine learning method, case study location, and performance metrics.

In the case of the pre-fire prevention and preparedness stage, the main applications identified were segmented into the following categories: wildfire fuel modelling, risk assessment and ignition prediction of wildfires, support to dispatch, landscape planning and prevention measures for severity mitigation, and inventory data. In the case of the stage of management of active wildfires, the main applications were segmented into wildfire detection, spread prediction, and suppression. Finally, in the case of the post-wildfire stage of restoration and adaptation activities, the main applications were segmented into the analysis of burned area and severity, impacts related to social factors, impacts related to carbon fluxes, and impacts related to forest conditions.

The literature highlights that the main machine learning methods used for wildfire management decision support are random forest, support vector machine, and neural networks, and that both classification and prediction are explored. Overall, there is a trend towards the use of ensemble modelling to improve the accuracy of the models, as well as towards the integration of remote sensing imageries, machine learning, and geospatial analysis to identify areas that are prone to wildfire occurrence. The literature highlights further the potential for the association of multiple modelling methods to obtain a more accurate set of candidate models for the same area, to provide a more refined sampling in order to choose a final model.

There are still many challenges associated with a wider use of machine learning methods. Constant improvement is needed, mainly to obtain faster models while improving the interpretability of the results. There must also be a focus on the study of the computational time required for the modelling process, as well as a trade-off analysis between the computational time, platform simulation, feature selection, and management prescriptions related to the results obtained by the models.

Substantial steps are being taken to promote the use of machine learning methods within the framework of wildfire modelling applications. This review concluded that there is an obvious potential for adopting machine learning methods for forecasting and classification and for enhancing management decision support. It listed further challenges related to the fulfillment of this potential.

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