Highlights

Leveraging the Power of Internet of Things and Artificial Intelligence in Forest Fire Prevention, Detection, and Restoration: A Comprehensive Survey

Sofia Giannakidou,Panagiotis Radoglou-Grammatikis,Thomas Lagkas,Vasileios Argyriou,Sotirios Goudos,Evangelos K. Markakis,Panagiotis Sarigiannidis

- **AI in Wildfire Science and Management**: The purpose of this survey is to present a thorough review of the various AI models utilised in wildfire science and management. Its objective is to offer a clear comprehension of the current state-of-the-art in applying AI to this field.
- **Evaluation of Accuracy and Reliability of AI Models in Wildfire Science**: This survey aims to evaluate the accuracy, reliability, and applicability of AI models in different contexts. Analysing the advantages and limitations of these models will allow for informed decision-making when selecting the most suitable models for particular applications.
- **Limitations and Challenges of Selected AI Models in Wildfire Science**: The primary objective of this research is to identify the limitations and difficulties of the selected AI models in the field of wildfire science and management. Its purpose is to provide recommendations for future research in this field and to assist in the development of new models that can better address the unique challenges it presents.
- **Advancements in the Application of AI in Wildfire Science and Management**: The purpose of this study is to advance our understanding of the application of artificial intelligence in wildfire science and management. It presents a summary of the previous research and underlines the future implications of AI in this field.
- **Directions for Future Research Work through Novel Technologies**: Based on the lessons learned from this analysis, directions for future research work in this field are provided, taking full advantage of novel technologies, such as 5G, Software Defined Networking (SDN), digital twins, federated learning and blockchain.

Leveraging the Power of Internet of Things and Artificial Intelligence in Forest Fire Prevention, Detection, and Restoration: A Comprehensive Survey[★,★★]

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ABSTRACT

Forest fires are a persistent global problem, causing devastating consequences such as loss of human lives, harm to the environment, and substantial economic losses. To mitigate these impacts, the accurate prediction and early detection of forest fires is critical. In response to this challenge and living in the digital era of Artificial Intelligence (AI) and smart economies, there has been a growing interest in utilising AI mechanisms for forest fire management. This study provides an in-depth examination of the use of AI algorithms in the fight against forest fires. In particular, our paper starts with an overview of the forest fire problem, followed by a comprehensive review of various systems and approaches. This review includes a thorough analysis of the various works that have evaluated the factors that influence fire occurrence and severity, as well as those that focus on fire prediction and detection systems. The paper also explores the use of AI in adapting and restoring after the occurrence of forest fires. The paper concludes with an evaluation of the potential impact of AI on forest fire management and suggestions for future research directions, taking full advantage of novel technologies, such as 5G communications, Software Defined Networking (SDN), digital twins, federated learning and blockchain. Finally, the paper draws lessons and insights on the potential and limitations of AI in forest fire management, highlighting the need for further research and development in this field to maximise its impact and benefits.

1. Introduction

Forests play a crucial part in preserving the planet's ecological balance. Natural and human factors can cause fires, and these fires pose a significant threat to valuable natural resources. Forest fires can be catastrophic, with severe adverse impacts on the environment, economy, and human lives. The effects of forest fires include global warming, loss of biodiversity, and damage to natural habitats. Prediction and detection of forest fires at an early stage are vital for mitigating fire damage and lowering the need for firefighting activities. The first step in preventing the spread of forest fires is to estimate the likelihood of their development using models that take into consideration weather and fuel availability. These models are crucial in preventing the ignition and spread of fires. Additionally, they can also be employed to forecast the behaviour of fires after they have already started, depending on the conditions of the environment in which they are burning. Detecting forest fires is the second strategy, aiming to quickly locate and identify flames and deliver an accurate fire alert to prevent their spread. Various techniques, including human observation, satellite systems, wireless sensor networks, unmanned aerial vehicles, and systems using charge-coupled device cameras and infrared detectors, are used to detect forest fires. With the increasing threat of forest fires, it is essential to investigate new approaches to forecasting, detecting, and monitoring forest fires. Research has been carried out to integrate data mining

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techniques, such as algorithms, with fire detection systems in order to achieve more precise and efficient outcomes. The use of these new technologies and systems can greatly improve the ability to detect fires early and ultimately help reduce the number of victims and destructive consequences caused by forest fires.

This paper aims to provide a comprehensive analysis of the usage of artificial intelligence in wildfire science and management. With the increasing frequency and severity of wildfires globally, effective fire management practices that integrate smart technologies are crucial for mitigating the impacts of wildfires. The aim of this study is to examine the different Artificial Intelligence (AI) models utilised in various areas of wildfire science and management, including prevention and preparedness, detection and response, and restoration and adaptation, and assess their reliability, accuracy, and practicality in diverse situations.

Contributions: Based on the aforementioned remarks, the contributions of this study are threefold:

- **AI in Wildfire Science and Management**: The purpose of this survey is to present a thorough review of the various AI models utilised in wildfire science and management. Its objective is to offer a clear comprehension of the current state-of-the-art AI applications in this field.

- **Evaluation of Accuracy and Reliability of AI Models in Wildfire Science**: This survey aims to evaluate the accuracy, reliability, and applicability of AI models in different contexts. Analysing the advantages and limitations of these models will allow for informed decision-making when selecting the most suitable models for particular applications.

- **Limitations and Challenges of Selected AI Models in Wildfire Science**: The primary objective of this research is to identify the limitations and difficulties of the selected AI models in the field of wildfire science and management. Its purpose is to provide recommendations for future research in this field and to assist in the development of new models that can better address the unique challenges it presents.

- **Advancements in the Application of AI in Wildfire Science and Management**: The purpose of this study is to advance our understanding of the application of artificial intelligence in wildfire science and management. It presents a summary of the previous research and underlines the future implications of AI in this field.

- **Directions for Future Research Work through Novel Technologies**: Based on the lessons learned from this analysis, directions for future research work in this field are provided, taking full advantage of novel technologies, such as 5G, Software Defined Networking (SDN), digital twins, federated learning and blockchain.

Organisation: The paper's structure is as follows: Section 2 of the paper presents the study's motivation and contribution to the field of AI in wildfire science and management. In Section 3, the methodological framework employed in this study to assess the accuracy, reliability, and suitability of AI models in various contexts is described. Section 4 provides an overview of the AI techniques used in the field of wildfire science and management. Section 5 discusses the use of AI models for wildfire prevention and preparedness. It provides an overview of the models used in this area, as well as their limitations and challenges. Section 6 discusses the use of AI models for wildfire detection and response. It provides an overview of the models used in this area, as well as their limitations and challenges. Section 7 discusses the use of AI models for wildfire restoration and adaptation. It provides an overview of the models used in this area, as well as their limitations and challenges. Section 8 provides a comprehensive discussion of the findings from the previous sections and provides suggestions for future research in the field of wildfire science and management. Section 9 summarises the study's key findings and offers concluding observations on the use of AI in the field of wildfire science and management.

2. Motivation, Impact and Contributions

Recent increases in the frequency and severity of wildfires prompted this study on the application of artificial intelligence to wildfire science and control. The amount of acres burned by wildfires in the United States has increased from approximately 3 million acres in the 1990s to over 8 million acres in recent years, according to the National Interagency Fire Center (NIFC). With climate change causing higher temperatures and more frequent droughts, the number of wildfires has increased globally, leading to significant economic, ecological and social impacts. In this context, effective fire management practices that integrate the latest technological advancements, including AI, are crucial for mitigating the impacts of wildfires.

A number of studies have analysed the impact of wildfires and the importance of effective fire management practices. For example, a study by the NIFC estimated the total direct and indirect costs of wildfires in the US to reach $20 billion in 2020 Center) (2020). Another study by the International Journal of Wildland Fire found that the global economic cost of wildfires was estimated to be $126 billion in 2015, which is projected to increase to $230 billion by 2030 Bowman, Balch, Artaxo, Bond, Carlson, Cochrane et al. (2019). These findings highlight the importance of investing in effective fire management practices.

In recent years, there have been many surveys and studies focusing on the use of AI in wildfire science and management. These studies have aimed to explore the potential to support various aspects of fire management, including prevention, detection, response, and restoration. Chang et al. Chang, Lee and Wu (2010) conducted one of the earliest comprehensive reviews on the use of algorithms in fire management, covering topics such as fire behaviour modelling, fire spread prediction and fire management decision support systems. The study suggests that AI has the potential to enhance fire management practices by offering more precise and dependable fire predictions and decision support tools. Li et al. Li, Zhang and Du (2016) conducted a notable survey that concentrated on the use of remote sensing data for fire detection. The study evaluated various algorithms such as support vector machines, ANNs and decision trees and reported that these methods hold significant potential to improve the accuracy of fire detection. Teixeira et al. Teixeira, de Freitas, de Almeida and de Souza (2020) conducted a recent study that focuses on the application of algorithms in the context of wildfire preparedness and response. The study provides a thorough review of various algorithms, such as random forests, decision trees, and neural networks, and highlights their potential to enhance the effectiveness of preparedness and response efforts during a wildfire event. These surveys demonstrate the growing interest in the application of these in the field of wildfire science and management and highlight the potential of these methods to improve fire management practices.

The major purpose of this study is to provide a comprehensive overview of AI applications in wildfire science and management. The paper examines AI models deployed in the field, namely in the areas of readiness and prevention, detection and reaction, and restoration and adaption. The study also seeks to evaluate the accuracy, reliability, and applicability of these models in different contexts. The contributions of this study are threefold. Firstly, the study provides a comprehensive overview of the various AI models used in the field of wildfire science and management. Secondly, the study critically evaluates the accuracy, reliability, and applicability of these models in different contexts, providing valuable insights for researchers, practitioners, and policymakers. Finally, the study highlights the limitations and challenges of the selected models and provides suggestions for future research in the field. By making these contributions, this study pushes the current state of understanding of the application of AI in the field of wildfire science and management forward.

3. Methodological Framework

As depicted in Fig. 1, the methodological framework adopted in this paper follows a systematic review, including six phases: (a) definition of the overall study, (b) definition of the criteria for the selection of the papers and studies included in the review process, (c) a comprehensive search and collection of relevant studies, (d) quality review of the previous studies, (e) through analysis of the selected studies and finally(f) the interpretation and analysis of the findings.

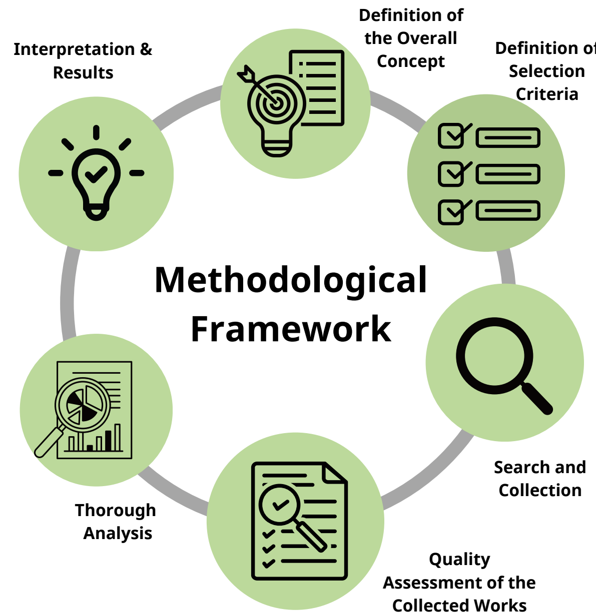

Figure 1: Methodological Framework

3.1. Definition of Overall Study

Fig. 2 illustrates the concept of the overall study in this paper, including three primary aspects: (a) Prevention and Preparedness, (b) Detection and Response, and (c) Restoration and Adaptation. In particular, the first aspect focuses on the prevention and preparedness models. In this aspect, the various types of wildfire prevention and preparedness models are analysed, including lightning prediction, fire weather prediction, fire management, fire occurrence prediction, wildfire preparedness and response, planning and policy, and social factors. The second aspect focuses on the detection and response models. More precisely, particular attention is paid to models regarding fire spread behaviour prediction, fuel characterisation, fire susceptibility mapping, fire perimeter and severity mapping and fire detection. Finally, for the third aspect, the aim is on restoration and adaptation models focusing mainly on climate change, soil erosion and deposits and smoke and particulate levels.

3.2. Definition of Selection Criteria

The second phase focuses on defining the selection criteria for the existing works chosen to be studied. In particular, the selection criteria can be separated into two main categories: (a) Inclusion Criteria and (b) Exclusion Criteria. The first category defines the characteristics that an existing work must have in order to be involved in the review process, while the Exclusion Criteria determine the characteristics that a study must not have to be involved in the review process.

- **Inclusion Criteria**: The inclusion criteria for our paper are to include existing works that (a) provide or propose (as a whole implementation or research study) environmental and ecological models that adopt approaches within the realm of AI regarding the foundational aspects defined above, namely (a) Prevention and Preparedness, (b) Detection and Response, and (c) Restoration and Adaptation.

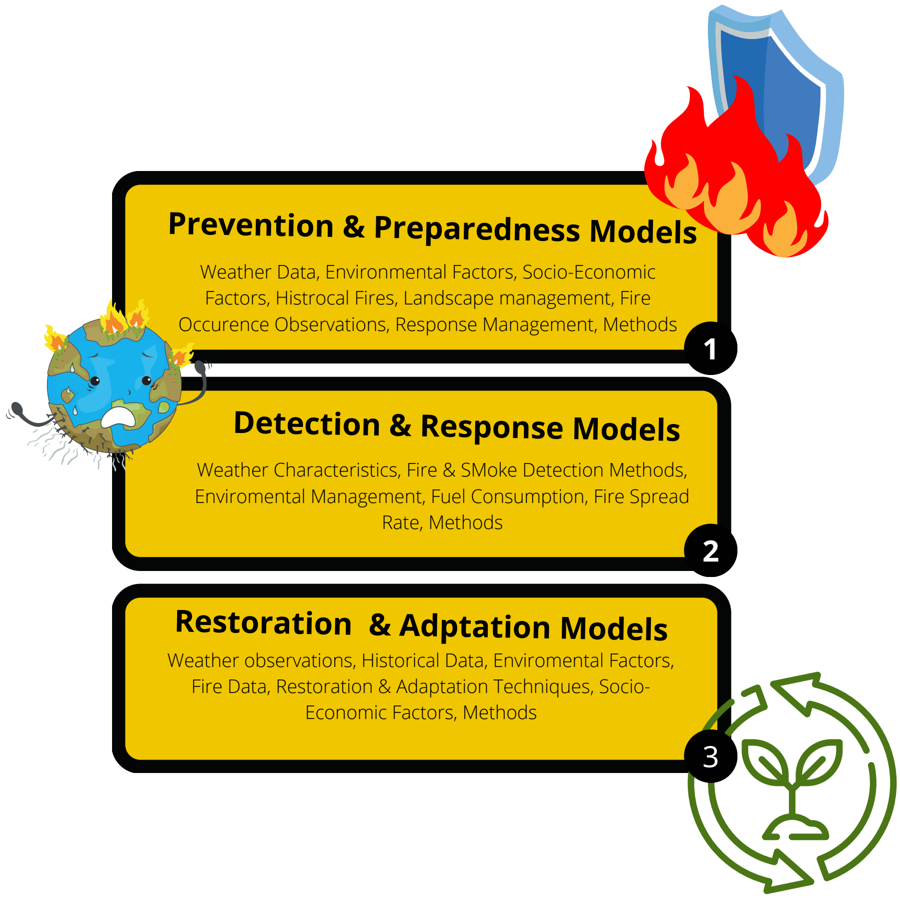

Figure 2: Concept of the overall study

- **Exclusion Criteria**: The exclusion criteria for our paper are not to include existing works that focus on other aspects related to environmental and ecological models. In addition, non-AI approaches are not included in this work. Finally, existing works that present significant methodological flaws, poor study design, inadequate sample sizes, or insufficient documentation are not included in this work.

3.3. Search and Collection

The next step is to search for and collect relevant works based on the overall concept of this study and the selection criteria presented above. This phase is critical in order to ensure that the study is comprehensive. Therefore, the search strategy includes and combines several keywords, such as: `wildfire`, `bushfire`, `forest fire`, `wildland fire`, `wildfire prevention and preparedness`, `fire weather prediction`, `lightning prediction`, `fire occurrence prediction`, `planning and policy`, `fire management`, `wildfire preparedness and response`, and `social factors`, `detection and response`, `fire spread behaviour`, `fuel characterisation`, `fire susceptibility mapping`, `fire perimeter`, `severity mapping`, `fire detection`, `restoration and adaptation`, `climate change`, `Soil erosion and deposits` and `smoke and particulate levels` combined with `machine learning`, `artificial intelligence`, `maximum entropy`, `decision trees`, `regression trees`, `neural network`, `random forest`, `deep learning`, `reinforcement learning`.

3.4. Quality Assessment of the Collected Works

Subsequently, after the collection of the various works, their quality review is necessary before their thorough analysis. This phase ensures that the proposed study is unbiased. In particular, three stages are involved in this phase:

- **Screening**: The titles, keywords and abstracts of the collected works are carefully checked to meet the inclusion and exclusion criteria.
- **Eligibility Assessment**: After the screening process, the full text of the paper(s) is considered to meet the inclusion and exclusion criteria.
- **Selection**: The works that meet the eligibility criteria are selected for thorough analysis.

3.5. Thorough Analysis

Next, a thorough analysis of the selected works is carried out. For this purpose, various factors are further investigated in terms of the overall concept of this study (Fig. **??**) and the inclusion criteria. In particular, regarding the wildfire prevention and preparedness models, the following technical factors are taken into consideration: (a) weather data, (b) environmental factors, (c) socio-economic factors, (d) historical fires, (e) landscape management, (f) fire occurrence observations, (g) response management and (e) AI methods. Next, regarding the wildfire detection and response models, the following factors are taken into account: (a) weather characteristics, (b) fire and smoke detection AI-based methods, (c) environmental management, (d) fuel consumption, (e) fire spread rate and (f) AI-based methods. Finally, six factors are considered regarding the wildfire restoration and adaptation models, namely (a) weather observations, (b) historical data, (c) environmental factors, (d) fire data, (e) socio-economic factors and (f) AI methods.

A detailed description of the data sources, methods, and techniques used in the analysis are being presented, as well as the statistical and computational methods used to evaluate the models. The limitations and challenges of the selected models are also discussed, along with the potential for future research in this field. A scoping review methodology was employed in this study to describe the literature in the fields of AI and wildfire science and management. Scoping reviews are particularly useful when the subject has not been thoroughly examined and the underlying concepts are complex and heterogeneous. A scoping review aims to identify gaps in published literature and provide a summary and dissemination of research findings.

3.6. Interpretation and Results

In light of the aforementioned remarks and following the overall concept of this study and the selection criteria, next, a detailed description of the data sources, methods, and techniques are presented, including statistical and computational methods used to evaluate the models. The limitations and challenges of the selected works are also discussed, along with the potential for future research in this field. In particular, over 200 relevant publications were identified and reviewed. In conclusion, based on the methodological framework presented in this section, this paper provides a comprehensive and up-to-date analysis of AI models and applications within wildfire science and management. The findings of this study will serve as a valuable resource for researchers and practitioners, highlighting the potential of AI techniques in the development of more effective and efficient wildfire models.

4. Overview of Artificial Intelligence, Machine Learning and Deep Learning Methods

Wildfires are a major threat to the environment, communities, and ecosystems. In an effort to mitigate the risks associated with these events, AI has been applied in various domains of forest fire prevention, detection, and restoration. This overview focuses on the use of AI techniques in forest fire modelling, specifically in the areas of prediction, detection, and response management Makridakis (2017).

One of the most popular AI techniques used in wildfire modelling is Machine Learning (ML)Khvostikov and Bartalev (2021). Machine learning algorithms have the potential to recognise patterns and correlations within data that can be leveraged to forecast the possibility of wildfires, the progression of fire expansion or the vulnerability of particular regions to fire Armas, Baeza, Nava and Moutahir (2013). These predictions can then be used to inform management and policy decisions, as well as assist in the planning of response actions. Decision trees, Random Forests, and Support Vector Machines are some of the most commonly used ML algorithms in wildfire modelling Bot and Borges (2022).

Another AI technique that has been applied in wildfire modelling is Artificial Neural Networks (ANNs) Zhang, Wang and Liu (2021). ANNs have been used to model the behaviour of fire spread, predict fire severity, and identify potential ignition sources. ANNs can also be used to process large amounts of data from various sources, such as satellite imagery and weather forecasts, and provide real-time predictions Zhang, Patuwo and Hu (1998).

Fuzzy Logic (FL) is another AI technique that has been used in wildfire modelling Juvanhol, Fiedler, SANTOS, Silva, OMENA, Eugenio, PINHEIRO and Ferraz Filho (2021). FL algorithms can be used to model the uncertainty and imprecision in data, such as the variability in weather conditions and fuel availability. FL can also be used to model the complex interactions between different factors that affect wildfire behaviour, such as topography and vegetation Parisien and Moritz (2009). Finally, Evolutionary Algorithms (EAs) have also been applied in wildfire modelling Pereira, Mendes, Júnior, Viegas and Paulo (2022). EAs can be used to optimise management and response decisions by simulating different scenarios and identifying the best course of action. EAs can also be used to improve the accuracy of predictions by tuning the parameters of models Montesinos López, Montesinos López and Crossa (2022).

Deep Learning (DL) is a branch of Machine Learning (ML) that has become increasingly popular in recent years because of its capability to learn and improve automatically from large amounts of data. In the area of forest fire modelling, DL techniques have been employed for image and video analysis, fire spread forecasting, and fire severity evaluation. Convolutional Neural Networks (CNNs) are one of the most commonly used DL methods in this domain. CNNs can automatically learn features from satellite imagery, aerial photos, or thermal imaging and use these features to perform various tasks such as fire detection and segmentation.

Forest fire prevention, detection, and restoration also follow a similar flow of processes as described for AI, ML, and DL methods. In this context, the three stages can be adapted as follows:

- **Pre-processing stage**: This stage transforms the input data, such as satellite imagery, weather forecasts, and vegetation data, into pre-established formats that are compatible with the targeted ML/DL model. The pre-processing methods used include normalisation, standardisation, min-max scaling, max abs scaler, and robust scaler to ensure the data is in a usable format.

- **Training stage**: In this stage, a model is trained using normal and abnormal pre-processed data, also known as features, to identify patterns and relationships that can predict the likelihood of a forest fire, its spread, or its impact on specific areas. Different ML/DL approaches can be used in this stage, including unsupervised and supervised detection methods, as well as semi-supervised novelty detection methods. For example, neural networks, decision trees, and Support Vector Machines can be used in the supervised detection category, while k-means, Stochastic Outlier Selection, Local Outlier Factor, Isolation Forest, and Angle-Based Outlier Detection can be used in the unsupervised detection category.

- **Prediction stage**: Once the AI model is trained, it can be deployed to analyse unknown data that has undergone the same pre-processing tasks. If the model output diverges from the expected values or identifies the input data as anomalies, it can raise the alarm to signal a potential forest fire. This information can then be used to inform management and policy decisions, as well as assist in the planning of response actions.

The use of AI, ML, and DL techniques in forest fire prevention, detection, and restoration can greatly improve the accuracy and efficiency of predictions, enhance the management of response actions, and optimise decision-making in forest fire management. The combination of different AI techniques, including DL, can address the complexity and uncertainty of forest fire systems, making them a valuable tool in the fight against wildfires.

5. Wildfire Prevention and Preparedness Models

Wildfires are natural disasters that can have devastating consequences for the environment, communities, and infrastructure. Effective prevention and preparedness strategies are crucial in mitigating the impacts of these events. Wildfire prevention and preparedness models play a significant role in this regard, providing valuable information to support fire management and planning efforts Bova and et al. (2010). These models use a combination of meteorological, fuel, and human activity data to predict the likelihood of a wildfire occurring in a specific area Chuvieco (2002). The models also consider the behaviour of the fire once it has started, including its rate of spread and the potential area that may be affected. This information is essential in guiding decision-making processes, including resource allocation, response planning, and the development of effective mitigation strategies Koutsias and et al. (2005). In addition to the physical factors, these models also consider social factors such as land use, population density, and human behaviour, which can impact the likelihood and severity of a wildfire McWethy and et al. (2010). The integration of these factors into the models enhances their accuracy and the effectiveness of the strategies developed from their results Radeloff, Hammer, Steward, Carter, Mladenoff and Stevens (2006).

The objective of this paper is to present a survey of different categories of models related to Wildfire Prevention and Preparedness. These models include fire weather prediction, lightning prediction, fire occurrence prediction, fire management, planning and policy, wildfire preparedness and response, and social factors. Figure 2 illustrates these categories. The strengths and limitations of these models will be discussed, as well as their potential applications in real-world situations. It is important to note that the advancement and refinement of these models will continue to be a critical component of wildfire prevention and preparedness efforts, helping to ensure the protection of communities, ecosystems, and the environment.

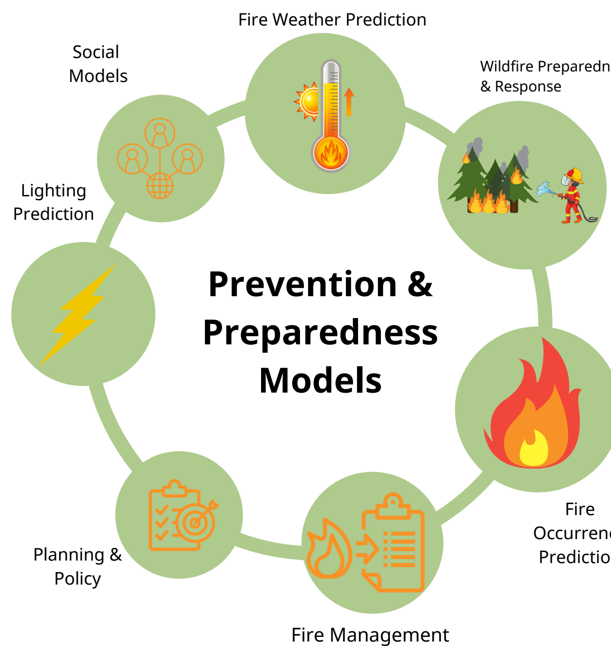

Figure 3: Prevention and Preparedness Models

5.1. Fire Weather Prediction

The prediction of fire danger conditions plays a crucial role in enabling forest management organisations to put into action plans for fire prevention, detection, and suppression before damage occurs. The ability to predict the potential for fires is based on various factors, such as weather conditions, lightning activity, land cover, fuel conditions, and human activity. Improved weather forecasting skills have created an opportunity to enhance early warning capabilities through the use of numerical weather prediction (NWP) Brunet (2005). The classification of fire hazards in different nations is often based solely on observed weather data Li, Meng and Wan (2010). The current fire condition classification is based solely on daily environmental monitoring, and satellite data on hot spots only provides a few hours of warning. However, the use of NWP can increase the early warning period to 1-2 weeks, enabling better coordination of resource sharing and mobilisation within and between countries Brunet (2005). Accurately predicting upcoming storms and lightning strikes is essential for estimating the frequency of wildfires, as lightning is the second leading cause of these events Mills (2010). For this purpose, electronic lightning detection systems have been widely implemented worldwide for many years to gather substantial location-time data on lightning strikes, serving the purpose of predicting fires. This information can be used to build regression associations with atmospheric conditions and stability indexes and to anticipate NWP using lightning prediction models Mills (2010). Therefore, it can be concluded that by using a combination of NWP, satellite data, and electronic lightning detection systems, early warnings of fire danger conditions can be improved, and effective action plans can be put into place. This can help to minimise the damages caused by wildfires and ensure the safety of people, wildlife, and the environment.

Wagner Van Wagner (1987) developed the Fire Meteorological Index (FWI) using weather variables to predict bushfires, which includes the Canadian FWI measurement Lawson and Armitage (2008). The FWI system and the Canadian fire forecasting system make up the fire hazard evaluation system. The index has been successfully used in Europe and North America, where observation sites are abundant. Fire weather is crucial in determining when and where a fire may occur and how quickly it will spread. Surface weather stations collect fire weather observations, which are then added to a map of the region. NWP models are used to forecast future fire weather conditions, but calculations with memory, such as the moisture indices of the Fire Weather Index (FWI) System, may contain errors. It is remarkable that surface fire risk can be related to broad-scale climatic and meteorological patterns.

San Miguel Ayanz San-Miguel-Ayanz, Schulte, Schmuck, Camia, Strobl, Liberta, Giovando, Boca, Sedano, Kempeneers, McInerney, Withmore, de Oliveira, Rodrigues, Durrant, Corti, Oehler, Vilar and Amatulli (2012) developed the European Forest Fire Information System (EFFIS) to meet the requirements of European bodies such as the European Parliament, the Monitoring and Information Centre of Civil Protection and the European Commission services, as well as relevant fire services in countries like civil protection services and forest fires. The EFFIS model encompasses the whole forest fire management cycle, from prevention and readiness to post-fire damage assessment and adaptation. It offers data to more than thirty countries in the Mediterranean and European regions and extracts forest fire data from twenty-two European nations. EFFIS seeks to increase forest fire prevention and control in Europe by delivering timely and accurate forest fire information. The model uses geographic data systems and remote sensing to support its essential applications. Two meteorological forecast systems, the Deutsche Wetter Dienst Kathleen, Patrick, Tanja and Michael (2021) and the French Météo-France Gourley, Tabary and du Chatelet (2006), estimate fire danger forecasts. Météo-France provides weather forecasts up to one week in advance and considering the Canadian FWI, this information can help to calculate a typical European fire danger index. Near-real-time applications such as rapid damage assessment and fire detection utilise information provided by the MODIS sensor in the AQUA and NASA TERRA satellites to locate hot spots (active fires) and map burned areas Salem, Barbara and Lipton (1992). The technology analyses two full patterns of Europe every day and offers data on scorched areas produced by big fires over 400,000 square metres. The architecture of the system is founded on online data services that allow access to real-time data via web feature services and web mapping.

The potential for automatically classified synoptic systems to predict fire weather is evaluated in Crimmins et al.'s study Crimmins (2006). This study explores the association between daily surface fire-weather index values and matching synoptic circulation patterns in the southwestern United States, as well as the circulation patterns connected with three recent wildfire occurrences. The study suggests that understanding critical fire-weather patterns is crucial for preventing future wildfires, and using weather forecasts before prescribed burns can help anticipate changes in fire-weather conditions. Due to limited long-term records, the analysis is restricted to case studies, but identifying these patterns may aid in planning necessary burning actions. For instance, the Cerro Grande fire, which caused extensive damage in Los Alamos, New Mexico, was fueled by strong winds, highlighting the importance of recognising critical circulation patterns.

Nauslar and colleagues Mejia (2018) used self-organising maps (SOMs) to examine the relationship between North American monsoon (NAM) events and significant wildfire incidents in the Southwest Area (SWA) and its Predictive Services Areas (PSAs). The study analysed various definitions and thresholds for identifying NAM events and significant wildfires and identified synoptic atmospheric patterns associated with NAM onset and wildfire events. The results provide decision support information for fire weather meteorologists and enhance understanding of the effects of atmospheric patterns associated with NAM on wildfire activity, which can aid in resource management and logistical planning to combat wildfires.

5.2. Lightning Prediction

Lightning prediction plays a crucial role in wildfire prediction as lightning is one of the leading causes of wildfires. Accurately forecasting the timing and location of lightning strikes can provide valuable information for predicting the onset and spread of fires. Electronic lightning detection systems, which have been used extensively around the world for many years, provide valuable information on lightning strike locations and times. This information can be used to develop lightning prediction models that use regression methods to associate atmospheric conditions and stability indices with lightning strikes. These models can be used to anticipate the occurrence of lightning and, thus, improve predictions of wildfires. For instance, Niamir Niamir and Niamir-Fuller (1999) used lightning data to develop a regression-based lightning prediction model. In another study, Baker Baker (1991) used a similar approach to forecast lightning strikes in the western United States.

Blouin et al. Blouin, Flannigan, Wang and Kochtubajda (2016) found that lightning is a significant cause of wildfires in Canada, accounting for 45% of documented wildfires and 71% of the burned area. To reduce suppression costs, lightning-caused fires should be prevented through primary attacks. The authors developed thunderstorm forecasting models for the period from April to October, using geographic and temporal covariates, weather-related reanalysis, and radiosonde observations. The models, which were developed and tested for the Alberta region of Canada, used cloud-to-ground lightning strikes from the Canadian Lightning Detection Network as inputs and achieved hit rates of up to 85%. The study identified many factors, including latitude, Julian day, the Showalter index, elevation, convective available potential energy, and longitude and developed the models using a random forest classification approach.

Bates et al. Bates, Dowdy and Chandler (2017) acknowledge that lightning of any level is considered a very frequent cause of conflagration worldwide. This study focuses on the analysis, as well as the possibility for prediction of the aforementioned phenomena, across a significant variety of locations. The research was conducted through the utilisation of statistics and ML. Upon deciding that the actual amounts of water falling during a storm are irrelevant, the data were classified into two categories: 'wet' and 'dry'. The main sources of input data used during this research include atmospheric variables from the ERA-Interim reanalysis, the number of recorded lightning bolts on a daily basis, and data from ground-based sensors. The atmospheric fields' features were defined through the use of appropriate low-dimensional data. The classifiers were evaluated by using ten-fold cross-validation across four different prediction skill scores. For further evaluation, the outputs were also compared with those of a different method utilised in one of the researchers' older studies regarding the Pacific Northwest, United States. While neither of these approaches proved to be superior to the other, it was discovered that both of them could potentially provide accurate predictions based on independent datasets. Additionally, the most vital variables for predicting dry lightning activity turned out to be the mean atmospheric field quantities.

5.3. Fire Occurrence Prediction

Fire Occurrence Prediction (FOP) models play a crucial role in wildfire preparedness and response. Nearly a century ago, FOP models were first developed to predict the number and location of fire ignitions in advance. Forecasting fire activity is a critical aspect of resource management and requires accurate predictions of weather conditions and lightning. Briones Briones-Herrera, Vega-Nieva, Monjarás-Vega, Flores-Medina, Lopez-Serrano, Corral-Rivas and Carrillo-Parra (2019) notes that regression techniques are frequently employed in these models to establish a relationship between a response variable (e.g., fire incidents or hotspots) and various weather and lightning-related factors at a specific geographic location or as a spatial probability. These predictions help in the preparation of resources, moving resources, and the readiness for potential fire activity. FOP models have evolved over the years and now incorporate more sophisticated algorithms and data sources, including remote sensing data and weather forecasts Niamir and Baker (2017). In recent years, ML techniques have been increasingly used in FOP models, leading to improved accuracy and reliability of fire predictions Niamir and Baker (2017). The use of FOP models has greatly assisted fire managers and policymakers in making informed decisions and reducing the risk of wildfires.

Alonso-Betanzos et al. Alonso-Betanzos, Fontenla-Romero, Guijarro-Berdiñas, Hernández-Pereira, Inmaculada Paz Andrade, Jiménez, Luis Legido Soto and Carballas (2003) analyse an application developed for the specific task of assisting firefighting forces against conflagrations in Galicia, Spain. The region is infamous for its large number of forest fires, particularly during the 1990s, a problem that continued to grow despite attempts by the people to suppress it. Galicia is regarded as one of the regions most severely affected by wildfires, not only in Spain but throughout Europe. Through the use of Expert Systems and ANNs, the system was built with the aim of backing up firefighting groups and wildfire monitoring procedures. The network attempts to predict forest fire risks in the hope of offering valuable intel for the aforementioned groups, as well as providing assistance in regard to the recuperation of areas damaged by fires in the past. The model was trained upon meteorological data and was tested with real-world datasets. Its produced results are satisfying enough, with the only inconvenience being an intrinsic error caused by the high frequency of wildfires in the particular region.

According to Vasilakos Vasilakos, Kalabokidis, Hatzopoulos, Kallos and Matsinos (2007), preventing wildfires is crucial for controlling them and other natural hazards. To identify regions with a high risk of fire ignition and take necessary precautions, fire risk rating systems are being developed in various countries for wildfire prevention and suppression planning. In the Lesvos Island region of Greece, the authors created a fire ignition risk scheme that can be expanded into a quantitative Fire Danger Rating System. The suggested method considers the geographical risk of fire, irrespective of the cause or expected burned area, and uses meteorological data to make predictions. The approach yields the Fire Ignition Index, which is derived from the Fire Hazard Index, FWI and Fire Risk Index. These indexes enable a systematic, comparative and quantitative evaluation of fire hazard rather than simply a proportional likelihood of fire occurrence. As part of its input parameters, the suggested system utilised remote sensing data from high-resolution QuickBird and Landsat ETM satellite sensors, as well as data from Remote Automatic Weather Stations and the SKIRON/Eta weather forecasting system. Geographic information systems were employed to perform spatial analysis and other operations on these inputs. To analyse the relationship between the input parameters and the probability of wildfires, neural networks were trained using historical data.

Vecin-Arias Vecín-Arias, Castedo-Dorado, Ordóñez and Rodríguez-Pérez (2016) focuses on the frequency of wildfires caused by lightning, specifically in the Iberian Peninsula's central area. The study focused on developing and analysing a prediction model to assist in lightning-induced fire occurrences. A 4 x 4 km grid cell was used for model training, showing data on the presence or absence of lightning-induced fires, and a 10 x 10 km grid was used for validation, both based on recorded data from 2000-2010. The two types of ML models used for the purposes of this research were the Random Forest and Logistic Regression methods. Across both of them, the most important variables were noticed to be the percentages of coniferous woodlands as well as the landscapes' agricultural crops. Due to this, it was deduced that vegetation type is a vital element for rating lightning-induced fire risk. Also, out of the seven independent variables utilised, five of them were used by both methodologies. The possibility of a wildfire caused by thunder was highly dependent on the following variables: the amount of produced agricultural crops, the level of altitude, the percentage of mixed woodlands and coniferous, and finally, the mean peak current of negative flashes. The presence of the first two decreased the danger percentage, while the latter two increased it. The misclassified predictions' spatial analysis showcased that the Random Forest model performs slightly better, making it more ideal for predictions in this particular matter, and as such, the experiments were deemed useful for assisting in the realisation of improved wildfire management solutions in the future.

Severe weather conditions are one of the main causes of wildfires, a problem that has only worsened with time due to climate change, endangering even seemingly safe areas. Van Beusekom et al. Grizelle (2018) analyse the relationship between the weather and the probability of conflagrations in the Caribbean, more specifically, the island of Puerto Rico. An ML model was developed in an attempt to be able to warn of such cases in advance. The model is trained on climatic information and other metrics of significance from Puerto Rico between 2003 and 2011. It processes its input with the aim of figuring out how each of these variables correlates to the possibility of a wildfire occurring. The model uses the Random Forest Classifier approach and utilises climate measurements exclusively. It was deduced that climate space was one of the most important variables, showing promising potential in regard to FOP. Other key factors include the sudden change of weather patterns, as well as the intensity and extent of said patterns. The classifier showcases promising results for predicting if a fire will occur, with a prediction rate of 80–89%. Additionally, the possibility of correctly estimating that the fire will be over 5 ha stands at 64-69

Dutta et al. Dutta, Das and Aryal (2016) acknowledge that an important climatic change has been pinpointed by the increase in Australian bushfire numbers over the last decades. The lack of understanding of climate change's impact on Australian bushfires highlights the need for scientific research. Information on bushfire incidents, spatial and temporal patterns, and climate data are necessary to create accurate forecasts for future hot spots. Dutta et al. (2016) created a machine-learning model with two layers that could detect the correlation between fire incidents and weather data, resulting in highly accurate hotspot forecasts. The study also highlighted that Australian bushfires have risen by 40% in the last five years, especially during summer, indicating substantial climate change.

Davis et al. Davis, Yang, Yost, Belongie and Cohen (2017) present a series of renewed fire environment ML models based on knowledge gained from older research. For the training of said models, they used datasets of large-scale forest fires in the Pacific Northwest Region of America over the course of nearly three decades, specifically from 1971 until 2000. In regards to factors that could lead to a wildfire, both natural means, such as lightning density levels and the human element, were taken into account. The model also considers additional information, including the state of the climate, topography, and vegetation. The final result is a time series of maps that display how the different climate scenarios can affect important wildfire environments within the surveillance region. The ideal model produced relied on its regularisation multiplier (RM) being set to 2.0 Sun, Long and Jia (2021). This multiplier sets the penalty associated with utilising variables or their transformations, and the higher it is set, the flatter the model's predictions turn out to be. Other important variables include CBI, which represents the model accuracy for presence-only test data, and AUC, which stands for a classifier's ability to distinguish between the different classes. The CBI's most ideal value was 0.97 ± 0.02, and the AUC's was 0.77 ± 0.01.

5.4. Fire Management

The goal of modern fire management is to strike a balance between the necessary amount of fire in the environment and minimising the associated expenses and damages. Techniques like vegetation management, controlled burning, fire prevention, and fire suppression are used to achieve this balance. Fire management is a form of risk management whose objective is to maximise the benefits of fire while limiting its costs and negative effects. Decisions regarding fire management can be made at several scales, ranging from long-term strategy decisions to real-time operational decisions. The supply chain for fire preparedness and response is structured hierarchically. Taylor Taylor (2017) maps the spatiotemporal dimensions of 20 main decision types used in fire control, highlighting the complex nature of fire management decisions. Fire control models can be categorised as prescriptive or predictive, with the former determining the success or failure of the initial attack and the latter optimising helicopter routing to minimise crew deployment travel time. While machine ML methods have been implemented to address fire control issues, studies in this area have been relatively scarce compared to other wildfire-related domains. This presents a significant potential for ML to be used in innovative ways to address fire control issues Vos (2017).

Loehman et al. Loehman, Keane and Holsinger (2020) present a series of approaches regarding landscape modelling that address the management difficulties caused by complex ecological interactions and an uncertain climate future. These approaches consist of three separate methods, dubbed (i) historical-comparative, (ii) future comparative, and (iii) threshold detection. The comparative-historical approach involves comparing current or future conditions to those of the past, usually defined as the period before European settlement and is often supported by long-term ecological records like tree-ring data. This approach is used to establish a baseline for the range of historical variation. Adding more weight to the importance of earlier human-generated landscape transformations could further draw attention to this matter, extending the HRV envelope further into human history. In contrast, the future comparative approach involves simulating various potential future scenarios for decades or centuries to evaluate how ecosystems may respond to changes and assess the impact of management decisions. Meanwhile, the threshold detection method uses integral thresholds to identify the climate or disturbances that cause rapid and persistent transformations in ecological systems. One such transformation could be the loss of resilience. In general, it appears that a critical environmental threshold needs to be reached so that ecological attributes can showcase significant changes.

Finney et al. Finney (2005) studied the statistical relationship between fire behaviour probabilities and effects, as well as the reliance of quantitative fire risk analysis on characterisation. Unlike probabilities or historic numbers of discovered ignitions, a.k.a. fire occurrence statistics, fire behaviour probabilities lean on temporal and spatial factors, depending on them in order to control the spread of fires. Such factors include topography, the weather, fuels, the relative direction of fire, as well as points of ignition occurring off-site. The calculations needed for the spatial characterisation of fire probabilities, fire behaviour distributions, and value changes from these aforementioned fires are all vital for the development of quantitative risk assessment procedures. At present, however, calculating all these components poses a number of difficulties. Despite that, it's possible to carry out research on them via susceptible values instead of the probability of fire-related loss or fire behaviour. The authors suggest that studies aiming to simulate or characterise fire behaviour probabilities and distributions should aim to cover large landscapes. Although the proposed approach does not consider the probability of loss, it is possible to map the positions of valuable properties in relation to risks and opportunities to aid land management. However, calculating the cost-effectiveness of management measures to decrease fire damage is not ideal since it requires an anticipated net value shift.

5.5. Planning and Policy

Planning and policy models are essential tools for wildfire prevention and preparedness, as they provide valuable information to decision-makers to make informed decisions. These models help to understand the potential impacts of different management strategies on wildfire risk and can assist in identifying areas that are particularly vulnerable to wildfire. The use of these models is crucial in developing effective strategies for land use planning, resource allocation, and risk management. For example, fire management agencies can use planning and policy models to assess the effectiveness of existing policies and management strategies, identify areas for improvement, and allocate resources more efficiently. Studies have shown the effectiveness of planning and policy models in predicting the likelihood and severity of wildfire events. Abatzoglou et al. Abatzoglou and Williams (2016) employed a spatial regression analysis to investigate how climate, fuel, and human-caused fire ignitions are related in California. Carvalho et al. Carvalho, Flannigan, Miranda and Borrego (2017) designed a policy model to evaluate the efficacy of fire management tactics in Portugal. Meanwhile, Vos et al. Vos (2017) employed a multicriteria decision-making model to evaluate how fire management strategies affect the socio-economic and ecological systems in Portugal. Overall, planning and policy models play a crucial role in reducing the risk of wildfires and increasing preparedness and response efforts. It is essential for decision-makers to have access to accurate and relevant information to inform their decisions and develop effective wildfire prevention and preparedness strategies Ager and Romans (2010).

According to Bao et al. Bao, Xiao, Lai, Zhang and Kim (2015), the greater fire severity levels in the western United States can be linked to the protective state of forestlands as a result of past restrictions on logging. They indicate that increased biomass and fuel loading in less-managed regions, particularly after decades of fire suppression, contributed to this result. The Random Forests algorithm was used to examine the association between protected status and fire severity in pine and mixed-conifer forests of the western United States. Consideration was given to important topographical and climatic elements. Higher forest protection levels were related to lower severity values, despite having the largest biomass and fuel loads. The results show that current beliefs about the relationship between forest protection and fire intensity must be reevaluated in both fire management and policy.

Bradley et al. Bradley, Hanson and Dellasala (2016) acknowledged that protected forestlands in the western United States may contribute to greater fire severity levels as a result of historical logging limitations that raised biomass and fuel loading in less-managed regions following decades of fire suppression. To examine the association between protected status and fire severity, they applied the Random Forests algorithm to 1,500 fires affecting 9.5 million hectares in pine and mixed-conifer forests of the western United States between 1984 and 2014. Despite having the highest levels of biomass and fuel loading overall, they discovered that forests with higher levels of protection had lower severity scores. The study emphasises the necessity for a reevaluation of the connection between forest protection and fire intensity in fire management and policy.

Ruffault et al. Ruffault and Mouillot (2015) note that what approach to take to combat wildfires brought on by lightning is up to the managers of US National Forests. Political discussions have frequently been sparked by disputes between stakeholders (such as timber companies, homeowners, and wildlife biologists). Providing a high-fidelity simulation environment can reduce the multistakeholder problem by allowing stakeholders to explore a range of alternative policies and understand the associated tradeoffs. Support for quick optimisation of MDP policies is necessary for the aforementioned environment so that users may modify reward functions and see the resultant ideal rules. McGregor et al. evaluate SMAC's viability as a black-box empirical function optimisation technique for expedient MDP policy optimisation. Four stakeholder constituencies and five reward function components are presented in this study. The SMAC algorithm is then used to calculate the optimal policy within this set for the reward functions of each stakeholder group. This approach enables stakeholders to explore a range of alternative policies and understand the associated tradeoffs, ultimately reducing the complexity of the decision-making process. During the validation phase, it was proved that SMAC is capable of rapidly identifying excellent policies that make sense from a domain perspective. SMAC is used to construct a surrogate model from a small number of simulation runs of the full-fidelity simulator because the simulator is too expensive to support interactive optimisation Li, Wen, Wang, Liu and Yuan (2022). The policies are assessed on the full-fidelity simulator to ensure the effectiveness of the SMAC-optimised policies. The outcomes support the validity of the estimations of the surrogate values. This is the first time a full-fidelity simulation has been used to optimise wildfire management strategies. Other natural resource management issues can also use this technology in cases when high-fidelity simulation is prohibitively expensive Mario Miguel Valero (2021).

In order to assess the effectiveness of MFMCi, McGregor et al. McGregor, Houtman, Montgomery, Metoyer and Dietterich (2017) use the visual characteristics of the MDPVIS MDP visualisation in order to support interactive MDP visualisation. The authors used the unitless metric of visual fidelity error, which assesses how closely MDPVIS resembles the visualisation produced by the ground truth simulator under MFMCi. The authors use a time-consuming, computationally costly wildfire, wood, vegetation, and weather model to show off MFMCi. The purpose of the wildfire management simulator is to advise the US government's wildfire suppression rules, which determine whether or not a wildfire will be put out. According to the surrounding pixel layers and the hourly weather samples from 26 historical weather years, the fire simulator spreads fire spatially from an ignition site. Included in the list of weather factors are the hourly wind speed, wind direction, cloud cover, lowest and maximum temperatures, humidity, and precipitation. By modelling the weather time series and the locations of the ignition as exogenous factors, MFMCi was employed in this work to synthesise trajectories. Since neither human behaviour nor the physical environment, at least initially, has an impact on the weather, it is exogenous. Due to the fact that tree cover has no impact on the spatial probability distribution of the ignition, the location of the ignition is exogenous to the surrounding environment. Furthermore, the landscape's deterministic functions for harvesting timber and promoting plant development ensure that every change in state has an associated outcome.

5.6. Wildfire Preparedness and Response

Wildfire preparedness and response play a crucial role in reducing the negative impacts of wildfires on communities, infrastructure, and the environment Alexander and Gustafson (2003). Effective preparedness and response strategies are necessary to ensure that firefighting resources are effectively utilised and that communities are adequately protected from the impacts of wildfires Keeley and Fotheringham (2000). The allocation of firefighting resources is a complex task that requires the consideration of a number of factors, including the location and size of the fire, weather conditions, and the availability of firefighting resources Keys and DeBenedictis (1998). ANNs have been effectively utilised to predict and simulate regional patterns in the distribution of firefighting resources. For example, a study by Costafreda-Aumedes et al. Costafreda-Aumedes, Cardil, Molina Terrén, Daniel, Mavsar and Vega-Garcia (2015) used ANNs to simulate the distribution of firefighting resources in Spain. The study indicated that Spanish authorities frequently respond to major fires by expanding their resources when the flames spread in size or length; however, in current multiple-fire circumstances, resources may be diverted from their use on large fires Krawchuk, Moritz and Anderson (2011). However, evaluations conducted at the national level could obscure the reality that regional firefighting resource patterns vary across Spain. Effective fire prevention strategies should be a top priority for all regions at risk of wildfires. A review of the whole suppression policy in effect is necessary, as current strategies may not be sustainable in the long run, especially as budgets become more restricted and hazard levels increase Murphy (1995). As stated by Jose et al. Olabarria (2019), simply adding suppression resources when fires grow in size or duration will not be effective in the long run, and other strategies must be considered to reduce the risk and severity of wildfires.

Penman et al. Penman, Nicholson, Bradstock, Collins, Penman and Price (2015) present a series of methods which calculate the risk assessment of multiple fire management methods, as well as mitigate house damages due to wildfires. The authors introduced spatial data and developed a process model that generates expert opinions in order to assist in handling the aforementioned task. Experiments were conducted on BNs, which provide an ideal framework for what the paper is aiming to achieve Caballero, Ferreira, Lima, Soto, Muchaluat-Saade and Albuquerque (2021). It should be noted that meaningful suggestions on the management field will stand in need of additional considerations, mainly due to the fact that the implementation of new actions will be limited by a number of outside factors, mainly economic, social and environmental. However, the results show promise, and it is also possible for researchers to adopt the developed strategies in fields researching different natural disasters, such as earthquakes, floods or droughts Chaudhary and Piracha (2021). However, at their current state, all strategies focus on calculating the point of loss and could benefit from potential future expansions that trade-off landscape management approaches like initial ignition attacks and fuel treatment.

O'Connor et al. O'Connor, Calkin and Thompson (2017) offer a possible solution to the problem of the rapidly evolving conditions that influence the decisions that need to be made in the event of active fire incidents. In the majority of cases, extreme fire weather conditions, fuels, and topography are all important factors directly dictating potential fire spread, as well as burn severity. The authors aim to use these factors to produce metrics representing the weight of fuel characteristics, topography, fire suppression effort, and road networks. The perimeter locations of 238 big fires were used to construct a predictive model of prospective fire control locations. This model covers a 34000 km2 large landscape in Northern Nevada and southern Idaho, and its features range from topographic and natural to fuel types and anthropogenic barriers to fire spread. The fire control probability surface can be used in order to better plan fire-controlling measures in advance, as well as a network of locations that align fire operations and land management. Additionally, the added information could be used to mitigate unnecessary exposure to danger for fire responders. In the end, the model managed to predict fire perimeter locations with an accuracy of 69% on an independent dataset. However, it didn't compensate for factors such as weather conditions during the various wildfires.

Rodrigues et al. Rodrigues, Alcasena and Vega-Garcia (2019) address the problem of wildfires escaping the borders of Initial Attacks (IA) and causing more damage than anticipated. To mitigate this, they developed an ML model that assesses the probability of fire containment by IA in Catalonia, using ML algorithms trained on historical locations of kindling and other ignition methods. The most significant variables were early detection, aerial support, and ground accessibility. The model produces gradients that show the lowest and highest chances of fire containment. Simulations of various weather conditions were conducted, indicating that parameters such as high wind speeds and temperature could cause an escape from IA. In 17 years, 13 days had disastrous fire conditions, with five episodes burning 1546 ha. The model provides useful information for first responders and brings to light the current limitations of the fire exclusion policy in Mediterranean areas. The authors believe that their proposed model can assist in long-term management solutions for wildfires and fire response planning.

Julian et al. Julian and Kochenderfer (2018) acknowledge that a high-dimensional control problem is keeping an airplane under control using visual data. Deep reinforcement learning (DRL) is one approach that could be used to address this kind of issue. Using raw images as input, the algorithm formulates a plan to optimise the long-term accumulation of rewards, enabling precise control in high-dimensional state spaces. The control system is decoupled from wildfire observations using established methodologies for autonomous wildfire monitoring. Planning trajectories for aircraft around wildfires is a difficult task due to the unpredictable growth of fires and the limited data available for controllers to use. In addition, controllers adjusted manually using image features may not be universally applicable to all images. To overcome this issue, this study proposes a real-time method to generate bank angle commands from wildfire photographs, allowing multiple planes to coordinate and monitor the spread of fires effectively. A real-time guidance system for fixed-wing aircraft is introduced by the authors, which enables efficient wildfire surveillance. Additionally, a deep neural network is developed to optimise wildfire monitoring for pairs of aircraft using only sensor data. After developing and comparing the two approaches, it was demonstrated that the neural network controller used in the study could accurately guide the aircraft along the fire front. Potentially, the trained network might be linked to the guidance systems of actual aircraft to produce intelligent flight paths for monitoring wildfires.

5.7. Social Factors

The likelihood and severity of wildfire events are greatly influenced by social factors such as human behaviour, land use patterns, and community resilience, as noted in Smith et al. Smith and Huang (2019) research. To create effective strategies for prevention and preparedness, it's crucial to comprehend the social factors that contribute to the occurrence and propagation of wildfires. Leithead, Gaffney, Tawn and Beniston (2020). Social factors models are tools that can be used to predict and understand the impact of social factors on wildfire risk and to identify areas that are particularly vulnerable Klare and Ledford (2018). These models can also inform management and policy decisions related to wildfire prevention and preparedness, including decisions about land use planning, community outreach, and education Bond and Bond (2018).

With the use of an ad hoc BN model that was developed from a dataset, Delgado et al. developed the following archetypes for triggered forest fires. Shye's model of the action system utilised arsonist motivation, which is a crucial factor in psychological criminology and the most significant author variable in the model, to establish archetypes based on the modes of operation in criminal acts. The authors also succeed in validating the five archetypes, albeit with certain particularities, owing to the methodology's considerable potential. Although the built BN models demonstrate the correlation between the various variables, such as wildfire characteristics and the arsonist's characteristics, including motivation, as well as the accurate understanding of these dependencies, it is still possible to make predictions about some variables based on others without neglecting to take into account the intricate relationships that exist among them. In actuality, the BN model captures this complexity and makes effective use of it Afzal, Yunfei, Nazir and Mahmood (2019).

The Social-Climate Related Pyrogenic Processes and their Landscape Effects (SCRPPLE) is a new fire model created by Scheller et al. Scheller, Kretchun, Hawbaker and Henne (2019) that emphasises the social aspects of fire and includes human ignitions, whether accidental or caused by prescribed fire, as well as the spatial and temporal patterns of prescribed fires, the effects of fuel treatment, and the spatial patterns of fire suppression. Additionally, terrain, fuel, and climatic influences are all captured by SCRPPLE. The authors emphasised parameterisation using newly available, more readily available landscape-scale information. The strategy places concentrated attention on several procedures. It may be easily deactivated if suppression is not used in the landscape. The link between ignitions, spread, and the FWI was the only information necessary to run the fire model given FWI. Every modelling technique has its own set of restrictions, and SCRPPLE is no exception. For adequate parameterisation, it needs a significant amount of geographical and temporal data. However, the extensive collection of remotely sensed images over active fires has already fulfilled these data requirements.

Using the multi-criteria evaluation technique, Faramarzi et al. Faramarzi, Hosseini, Pourghasemi and Farnaghi (2021) conducted an applied study to identify the Golestan National Park's possible fire threats by taking into account environmental, climatic, and human aspects. The study revealed the significant impact of human activities on the spread of wildfires in the study area, with the transit road being the most influential factor. The study highlights the importance of taking all factors into account when it comes to wildfire occurrence, as evidenced by the need to eliminate the park's road. It also indicates that Ordered Weighted Averaging scenarios with low risk and minimal tradeoffs tend to perform better on average. The evaluation of fire risk mapping and assessment showed that while each method's maps are practical, their accuracy varies, and they can be employed in different situations to calculate fire risk based on human, climatic, and environmental factors. In regions where human factors are more important than other elements, for instance, preventative and management programs utilising warning technologies may be taken into account. Additionally, creating natural cut fires, planting species that can withstand fire, creating maps of wind patterns and days with high temperatures, and other tactics might be helpful in preventing forest fires Schoennagel T (2017). Designing water tanks or constructing helicopter landing pads in high-risk regions for wildfires might be considered as a realistic management strategy to deal with this problem in the park and put out the fire as fast as possible.

The following table characterises different types of Wildfire Prevention and Preparedness Models, providing a comprehensive overview of the various approaches used to mitigate the risk and impact of wildfires. These models encompass a wide range of factors, including weather data, environmental conditions, socioeconomic factors, historical fire records, landscape management practices, fire occurrence observations, response management strategies, and the methods used to predict and prevent wildfires. The table serves as a valuable resource for individuals and organisations seeking to understand the various approaches used to prevent and prepare for wildfires, and the factors that influence their effectiveness.

Table 1: Summary of Prevention and Preparedness Models

Reference	Weather Data	Environmental factors	Socio-Economic Factors	Historical-Fires	Landscape Management	Fire Occurrence Observations	Response Management	Method
San-Miguel-Ayanz et al. San-Miguel-Ayanz et al. (2012)	French Météo-France and Deutsche Wetter Dienst	Moderate-resolution Imaging Spectroradiometer (MODIS) and Nomenclature of Territorial Units for Statistics (NUTS)	The NUTS European Office for Statistics	The European Fire Database-25 years for Mediterranean countries	MODIS	The MODIS sensor and the Open Geospatial Consortium Sensor Observation Service	Monitoring and Information Centre of Civil Protection	EFFIS
Crimmins Crimmins (2006)	1988–2003 daily weather observations from 15 remote automated surface weather stations (RAWS) for the months of April, May, and June.	The National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR)	Not applicable	United States (Arizona and New Mexico) between 1988 and 2003.	RAWS sites (black dots) and NCEP–NCAR Reanalysis grid cells used in SOM classification	Not applicable	Southwestern wildfire regimes	SOMs algorithm
Nauslar et al. Mejia (2018)	National Weather Service Weather Forecast Office Tucson	NCEP	Not applicable	SWA PSA April through September from 1995–2013	SWA (Arizona, New Mexico, west Texas, and Oklahoma Panhandle)	Fire Program Analysis	the Southwest Geographic Area Coordination Center	SOM
Blouin et al. Blouin et al. (2016)	NCEP-DOEThe Canadian Lightning Detection Network	NCEP-DOE	Not applicable	From 1999 through 2011, thirteen years of lightning and weather data were collected.	Alberta province encompasses 661 848 km2 and contains six major Natural Regions.	Not applicable	Fire management agencies and communities	Random Forest (RF), Regression Tree,
Bates et al. Bates et al. (2017)	Ground-based CIGRE 500 by the Australian Bureau of Meteorology	Convective Available Potential Energy Ramezani Ziarani, Bookhagen, Schmidt, Wickert, de la Torre and Hierro (2019)	Not applicable	The records span January 2004 through at least December 2010 (Townsville) and no later than February 2013 (Melbourne).	Histograms for sites located in western Australia (Perth and Port Hedland) against those located in central and eastern Australia 458 (Darwin, Townsville, Coffs Harbour and Melbourne)	Not applicable	Fire management authorities	Low-Dimensional Summary Statistics Classification and Regression trees (CART), RF, linear discriminant analysis, quadratic discriminant analysis Nand logistic regression (LR)

Alonso -Betanzos et al. Alonso-Betanzos et al. (2003)	A self-contained component has been created to collect meteorological data through the Internet from automated meteorological stations in Galicia.	Databases which archive details concerning past firefighting measures, environmental information, meteorological data, terrain attributes, available resources, and so on.	Factors related to socio-economics and terrain such as the presence of a road, vegetation type, and so on.)	Information pertaining to fires that took place from 1988 to 2001.	Geographical Information System (GIS)	The Universal Transverse Mercator coordinates of the grid square where each fire transpired.	Not applicable	A neural network whose output is classified into four symbolic risks categories, CommonKADS methodology
Vasilakos et al. Vasilakos et al. (2007)	Real-time and predicted meteorological data were obtained from Remote Automatic Weather Stations and the SKIRON/Eta weather forecasting system.	Anticipated fuel moisture levels were estimated using the forecasted relative humidity data from the SKIRON/Eta model.	Assessment of the Fire Risk Index: the potential danger of fire in a particular location resulting from human activity.	Data on fires that took place on the island of Lesvos between 1970 and 2001.	QData obtained from QuickBird satellite on Lesvos Island, which has a Mediterranean climate characterised by warm, dry summers and mild, moderately rainy winters.	Not applicable	Not applicable	The multilayer perception neural network was trained using the back-propagation method to minimise error.
Vecín-Arias et al. Vecín-Arias et al. (2016)	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 with a resolution size of 200 × 200 m, provided by the National Geographic Institute	The lightning detection network	Not applicable	LR, RF

Van Beusekom et al. Grizelle (2018)	Daily climate surfaces from 2002 to 2011 were generated by interpolating the recorded daily maximum and minimum temperature and precipitation data obtained from National Weather Service Cooperative Observer stations across the island.	The National Digital Forecast Database	Utilisation of unemployment as a predictor for inferring socio-economic circumstances.	Information on the occurrence and size of fires between 2003 and 2011 in Puerto Rico, which includes data on almost 35,000 fires.	Located in the northeastern Caribbean Sea, Puerto Rico is the smallest of the Greater Antilles Islands, with the main island covering an area of roughly 8,900 square kilometres. The island features a narrow coastal plain, measuring between 8 to 16 kilometres wide, that is surrounded by steep igneous upland.	Not applicable	Not applicable	ANNs, Binary LR, RF, decisions Trees
Dutta et al. Dutta et al. (2016)	Not applicable	The NASA MODIS Active fire data product, which uses satellite images from EOSDIS, the Burned Area data product, and Australian Water Availability Project (AWAP) data.	Not applicable	Comprehensive investigation into the history of bushfires in Australia from 2007 to 2013.	The Fire Information for Resource Management System data and images obtained from the Land Atmosphere Near-real-time Capability for EOS system, which is managed by the NASA/GSFC/Earth Science Data and Information System.	NASA Active Fire and Burned Area data	Not applicable	An ensemble approach that employs a two-layered machine learning model to establish the correlation between fire incidence and climatic data.
Davis et al. Davis et al. (2017)	NASA Earth Exchange downscaled climate models	The fire environment of the 1971–2000 climate normal period.	Not applicable	The climate during fire season was determined based on the 1971-2000 climate normal data.	The forest land in Washington and Oregon covers an area of 216,900 square kilometres.	United States Department of Agriculture Active Fire Mapping Program	Not applicable	MaxEnt version 3.3, he Parameter-elevation Regressions on Independent Slopes Model

Loehman et al. Loehman et al. (2020)	Not applicable	FireBGCv2 landscape-scale, ecosystem-fire process model	The Coupled Natural and Human Systems Program, which is funded by the National Science Foundation.	A historical comparative methodology or approach.	FireBGCv2 landscape-scale, ecosystem-fire process model	Not applicable	Not applicable	The multivariate model was subjected to principal components analysis. Simulation modelling is a dynamic and evolving field that is faced with ecological complexities and the emergence of non-analogue system drivers and responses.
Finney Finney (2005)	Local weather records	Not applicable	Not applicable	Not applicable	Generate simulated random ignitions and artificial landscapes.	Not applicable	Not applicable	The development of a quantitative risk assessment method relies on the spatial characterisation of fire probabilities, fire behaviour distributions, and the changes in value resulting from those fires.
Bao et al. Bao et al. (2015)	Not applicable	The Greenpeace Research Laboratories and the United States Environmental Protection Agency (EPA) conduct research on climate change.	The Guangzhou Administration of Forestry and Municipality Garden is responsible for the construction project of the park social security and key forest zone video monitoring system in Guangzhou City.	In 2012, a total of 3966 forest fire incidences were identified in the Chinese forestry development.	Longdong Forest Park, located in the northeast of Guangzhou, China, is situated at the southern end of the Dayu Mountains and is covered by forest area, which constitutes 96% of the park.	The coverage rate of forest fire monitoring in China has increased from 45.3% to 63.1%. Models have been developed to determine the location of watchtowers.	Not applicable	Three specific application models have been developed for locating watchtowers in the context of forest fire monitoring.

Bradley et al. Bradley et al. (2016)	The PRISM climate group	Level III ecoregions, U.S. EPA	Not applicable	Between 1984 and 2014, approximately 1500 fires affected 9.5 million hectares of pine (Pinus ponderosa, Pinus jeffreyi) and mixed-conifer forests in the western United States.	Extent geographical of forest types derived from the Biophysical Settings (BpS) data collection, ArcMap 10.3	Not applicable	Not applicable	RF, Spatial autocor-relation (SA), Gap Analysis Program
Ruffault and Mouillot Ruffault and Mouillot (2015)	From the 8 8 km grid SAFRAN meteo-rological database, daily weather variables were produced (CNRM France)	PROMETHEE fire database	Globally, diverse national and regional fire policies have been formulated and implemented, according to Dynamic Global Vegetation Models	Historical fire activity from 1973 to 2006 according to national data.	PROMETHEE fire database	Not applicable	New fire practices (fuel management, prescribed burnings, ignition prevention and firefighting)	Dynamic Global Vegetation Models, boosted regression trees (BRTs)
McGregor et al. McGregor et al. (2017)	By resampling the historical weather time series observed at a local weather station, the weather is repro-duced.	A simulation platform with high fidelity in which stakeholders can explore the policy space.	Not applicable	Resampling from the historical weather time series observed at a nearby weather station is utilised to mimic the weather.	Each of the approximately one million pixels on the landscape has thirteen state factors that influence the spread of wildfires. (Open-StreetMap)	Not applicable	Sampled 360 policies from a class of policies that suppresses wildfires depending on the Energy Release Component at the time of ignition and the day of ignition.	MFMCi surrogate model, SMAC—a black-box empirical function optimi-sation algorithm
Costafreda-Aumedes et al. Costafreda-Aumedes et al. (2015)	National Wildland Fire Statistics Estadística General de Incendios Forestales (EGIF)	National Wildland Fire Statistics (EGIF)	Autonomous communities without neighbouring similarities and few large fires (fewer than 100) were considered in a general model for the whole of Spain.	National Wildland Fire Statistics (EGIF) of the Agency for Protection against Forest Fires of the MAGRAMA in the period 1998-2008..	Combining the presence of medium-scale farming regions, areas with limited natural vegetation cover (grasses and range lands), broad shrub lands and park-like open forest structures with undergrowth.	Not applicable	emergency agencies or forest services, the Ministry of Environment and Rural and Marine Affairs, the Ministry of the Interior's Civil Protection, and the Army Emergency Unit.	ANNs
Penman et al. Penman et al. (2015)	Richmond Bureau of Mete-orology weather station (station number 67033)	The McArthur Forest fire danger index, GIS data or Google Earth	If a resident prepares for wildfires and the community education level is adequate, the resident is prepared.	daily Forest fire danger index 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	Not Applicable	Bayesian Networks (BNs)

O'Connor et al. O'Connor et al. (2017)	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 a 34 000 km2 landscape straddling Idaho, Nevada, and Utah in the northern Rocky Mountains	Not applicable	Not applicable	BRT and the MaxEnt package
Rodrigues et al. Rodrigues et al. (2019)	Daily ERA-Interim grid data from the European Centre for Medium-Range Weather Forecasts at midnight.	Wildland agriculture interface mosaics, herbaceous crops (mostly cereal crops), forests, shrublands and grasslands.	Human-caused fires are consequently lit around urban populations or roadways.	Spanish EGIF database	The Spanish National Topographical Database 1:25,000 and the Spanish National Plan of Aerial Orthophotography were queried for geospatial data.	MODIS and the Visible Infrared Imaging Radiometer Suite (VIIRS)	The Spanish EGIF database	Spatial modelling with RF
Julian and Kochenderfer Julian and Kochenderfer (2018)	Not applicable	Not applicable	Not applicable	Not applicable	A 1 km2 parcel of land is subdivided into cells to make a 100100 rectangular grid.	DRL to guide the aircraft around a wildfire	Not applicable	A partially observable Markov decision process, DRL.
Delgado et al. Delgado, González, Sotoca and Tibau (2018)	Not applicable	Not applicable	Under the direction of the Prosecution Office of Environment and Urbanism of the Spanish state, a database of clarified arson-caused wildfires has been compiled.	Since 1968, the General Directorate of Natural Environment and Forestry Policy of the Spanish Ministry of Agriculture and Fisheries, Food, and the Environment has gathered statistical data on forest fires.	Not applicable	Not applicable	Not applicable	BNs
Faramarzi et al. Faramarzi et al. (2021)	Maps of temperature, rainfall, pressure, and moisture were prepared from meteorological data, WRPLOT	Global Positioning System (GPS) distance map of springs; NDVI map derived from 2017 Landsat 8 satellite photos	Main road, side road, village, camping, hunters, shepherds	The forest fire locations were identified according to field surveys, MODIS satellite images, and the historical fires recorded by the park authority during 1981 - 2018.	The springs distance map was produced with GPS, and the NDVI map was derived from 2017 Landsat 8 satellite pictures.	Not applicable	Not applicable	Ordered Weighted Averaging-scenarios, IDRISI Taiga, and ArcGIS (Version 10.4, 2019) software.
Wagner Van Wagner (1987)	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 behaviour indexes representing a rate of spread, fuel weight consumed, and fire intensity.	Not applicable	Consideration of FFMC, DMC, DC.

6. Wildfire Detection and Response Models

Forests play a crucial role in maintaining the ecological balance of our planet. However, forest fires often go undetected until they have already consumed a substantial amount of land, making them difficult to control and suppress. The damage caused by forest fires is devastating, not only in terms of the ecology but also in the environment and atmosphere Ryan and Rumker (2001). It has been estimated that 30% of the carbon dioxide (CO2) in the atmosphere is a result of forest fires, which also release significant amounts of smoke into the atmosphere. Forest fires have significant long-term consequences, such as changes in local weather patterns, worsening of global warming, and the disappearance of rare plant and animal species Giglio, Randerson and van der Werf (2015). These fires often happen in isolated, uninhabited, or inadequately maintained areas, where dry and withered vegetation serves as fuel for their spread. These fires can be initiated by human error, such as improperly disposing of cigarettes, or natural causes, such as intense sunlight concentrated by broken glass. Once the fire has started, it can quickly spread and cause extensive damage. The fire initially spreads through the surface layer and can progress to a `crown fire` if not contained in its early stages Papagiannaki, Kalogerakis and Karantzalos (2018).

In order to reduce the impact of forest fires, various detection and monitoring techniques are employed by authorities, such as aerial and satellite surveillance, observers, and optical camera sensors. These techniques are categorised into two primary groups: volunteer and public reporting of fires, as well as public aircraft and ground-based field workers. Controlled burning, fire weather forecasting, watchtowers, optical smoke detection, lightning detectors, infrared detectors, spotter planes, water tankers, and smartphone notifications are some of the popular approaches for detecting fires at an early stage Malamud, Turcotte and Rinaldo (2010). The goal of these efforts is to identify forest fires in their earliest stages and increase the likelihood of containment before they become uncontrollable or cause serious damage. The establishment of guidelines, such as the one stating that it takes one minute to extinguish one cup of fire, highlights the importance of early detection and rapid response Kalogerakis, Papagiannaki and Karantzalos (2015). With millions of hectares of forests devastated by fire each year, the need for effective fire detection and suppression methods is clear. Fig. 3 depicts the Detection and Response Models that were considered for this paper.

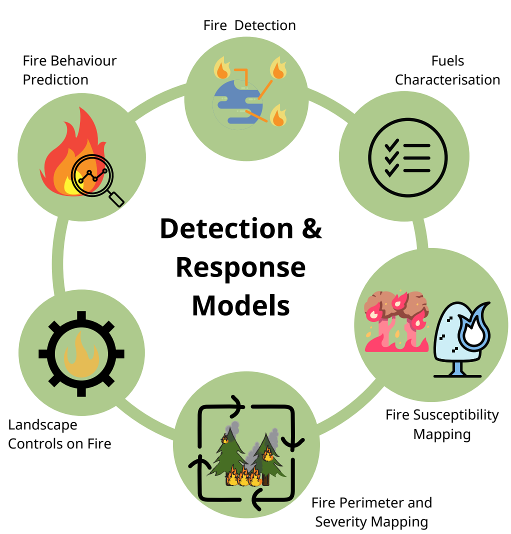

Figure 4: Detection and Response Models

6.1. Fire Spread Behaviour Prediction

The prediction of fire spread behaviour is a crucial aspect of wildland fire management, as it helps in reducing the deployment of suppression resources and enables proper planning of evacuations in advance. There have been numerous models developed over the years to predict fire spread, each utilising various methodologies Pyne and Goldammer (1997). Fire spread rates, growth prediction, burned area, and severity are among the primary areas of concern in these models. The behaviour of fire encompasses a range of physical processes and features, such as combustion rate, flame height, and fuel consumption. Remote sensing data is beneficial in this regard since it enables a more extensive observation of critical factors that are difficult to assess directly from the field in terms of both space and time. Landsat land cover data, NOAA weather measurements, and archived MODIS sensor data from several years are employed in these models. The ability to optimise the tasking and routing of platform-based sensors, such as satellites and UAVs, has made it possible to forecast future fire magnitudes and detect previously unnoticed fires. Accurately understanding the status of a wildfire allows for better allocation of suppression resources and effective fire management Krawchuk, Moritz and Parisien (2009). It is crucial to have an accurate and continuous understanding of a wildfire's dynamic status, which includes its type, location, speed of spread, direction, topography, combustible material, and weather influences, in order to efficiently and rapidly combat the fire Su, Yan and Zhang (2017).

According to Markuzon and Kolitz (2009), the ability to probabilistically estimate the future size of known or yet-to-be-observed fires allows for better tasking and directing of platform-based sensors such as satellites and UAVs. Increased sensor allocation to wildfires improves their state assessment, resulting in more efficient suppression resource allocation and better hazard observation and mitigation. Data mining techniques were employed to predict which fires are likely to expand, and satellite monitoring was used to determine if the data collected was sufficient for real-time monitoring of Earth phenomena events, such as wildfires. Remote data collection is an effective means of obtaining extensive coverage of essential variables in both space and time, which is difficult to achieve through direct ground measurements. The models employed archived MODIS sensor data from multiple years, combined with Landsat surface cover data and NOAA weather observations (2021) (NOAA). Accurately understanding and maintaining awareness of a wildfire's dynamic state, including location, type, and features such as the rate of escalation, ignitable material, direction, topography, and weather impacts, is crucial for managing the fire in a systematic and timely manner.

Time limitations, resource management, and exactitude factors affect forest fire spread forecasting in real-time. A framework of cyber is portrayed by Artés et al.Artés, Cencerrado, Cortés and Margalef (2016) for forest fire development forecasting, which merges input data that is collected from various sources like remote meteorological sensors and satellites. To facilitate the instantaneous sharing of outcomes, the gathered data must be structured for simulation tools that utilise parallel programming paradigms and computing platforms. The Two-Stage prediction framework, which comprises the Prediction and Calibration stages, is suggested. The Calibration stage utilises a Genetic Algorithm (GA) to optimise the most crucial parameters of a forest fire spread model by accurately reproducing recent events via a spatial optimisation objective function. The fitness function employed in the Calibration stage strives to minimise the discrepancy between the observed fire spread and the spatial fire development forecasted by FARSITE. However, because the GA is repetitive and the simulations take a lot of time, the Calibration stage can be time-consuming. To address this, a Time-Aware Classification (TAC) was integrated into the Calibration stage to allocate the number of cores to each individual in the population, considering time limitations. Despite the TAC approach being promising in ensuring that simulations are executed within the distributed time, it may become trapped in local optima in the search space. The RE-TAC approach overcomes the time constraint by using rescaled coarse-resolution data. While the TAC approximation may reject an accurate solution, the ReTAC method produces positive results when dealing with large forest fires. Compared to the TAC version, ReTAC reduces the error and achieves efficiency that is closer to the single core scheme where there is no time constraint. The prediction accuracy and time savings of ReTAC improve, depending on the computational capacity. ReTAC utilises high-performance computing platforms to take advantage of parallelism at two levels, with the implementation of a single forest fire propagation forecast parallelised using openMP. The two-stage prediction plan of ReTAC has been validated and proven to be an effective fire forecasting tool for forest fire function analysts and managers.

Houssami et al. El Houssami, Lamorlette, Morvan, Hadden and Simeoni (2018) present and compare the results of multiple sub-models developed by the authors with the aim of understanding the burning dynamics of conflagrations worldwide. Through the use of Forest Fire FOAM, the authors were able to base their research on a number of fire experiments that provided reliable results while also applying variable metrics for ambient and fuel. During development, the models adapted to a building block approach to their data handling, which assisted greatly with the understanding of forest fuel flammability. Houssami et al. El Houssami et al. (2018) showcased the importance of utilising appropriate submodels, as the different experiments employed a large variety of values for fuel bulk density and inlet flows. They also placed additional weight on the need to develop a multiphase fire modelling approach as well as the importance of further researching physics-based models in order to utilise fuel and environmental data.

In an attempt to predict and warn of possible fire propagation events in advance, Denham et al. Denham and Laneri (2018) present an application aiming to estimate the correct parameters considering this issue. The application in its current state is parallel and therefore has promising enough potential to achieve this in the future while also serving as a modular computing tool for open-source usage. Detecting ignition points and stochastic fire propagation parameters of past wildfires is a matter of vital importance, which solving will help tremendously in preventing such catastrophes. For this purpose, a highly adaptable tool called a parallel cellular automaton was used. With the model's dexterous capabilities of utilising spatial stochastic parameters, such as wind speed or fuel type, it became possible to study recorded wildfires with unknown starting points. Some identified troubling behaviour on the model's part is that if we try to use the ignition point coordinates as a parameter, the remaining input data identifiability decreases. There's a possibility that this can be improved by using an ensemble of several fitness functions to rank different simulations. Alternatively, it's worth testing fitting multiple fire scars to the model and testing its performance. Finally, fitting parameters such as times of fuel consumption is a matter of interest with regard to the future advancement of the application.

Ascoli et al. Ascoli, Vacchiano, Motta and Bovio (2015) applied genetic algorithms (GA) to the Rothermel Fire Spread Model, resulting in a system that can generate and fine-tune customised fuel models. The GA creates an initial population by generating model parameters with arbitrary fuel. This population is chosen based on its best members and is then edited and crossed over with several model parameter values. This process is repeated until the outcomes are satisfactory. The model was tested on three different fuel types: grass, shrubs, and litter. For each type, the GA improved the performance of the Rothermel Model, reducing the Root Mean Square Error by 19%, 26%, and 39%, respectively. The researchers also established a model that uses mixed grass and shrub fuel data, further optimised by GA. This model demonstrated significantly lower prediction errors when tested against a validation dataset. This new model utilised fire behaviour and fire data gathered from fire experiments in the dry heartlands of Southern Europe. In conclusion, GA successfully achieved its goal of calibrating fuel models for predictions via the Rothermel Model, thereby increasing their reliability. Furthermore, GA offers an easy method for adjusting fuel model parameters without requiring fuel sampling.

Kozik et al. Kozik, Nezhevenko and Feoktistov (2014) created a software method for building a fire model, ensuring real-time simulation of fire progression. The proposed method enables interactive manipulation of the model, making it feasible to quickly assess the efficacy of fire suppression techniques like clearing out forests, creating ditches, and starting an adversarial fire. Two learning methods are compared: traditional learning and learning using Kalman filters. The comparison is mainly focused on speed and accuracy, as these parameters are critical in a fire-fighting effort. Kalman filtering shows better convergence and stability of the learning process. For various wind speeds and surface reliefs, model experiments are conducted to identify potential fire development variations. It is shown that fire can pass over areas composed of unburned materials (such as ditches and rivers) because of the global nature of the connections in the neural network used to describe the fire. Assuming that the fire evolution can be continuously monitored by taking aerial or satellite photos of the fire zone, the produced model can be utilised to battle fires successfully.

Zheng Zheng, Huang, Li and Zeng (2017) recognises that quantitative modelling plays a crucial role in establishing efficient risk management plans and putting them into practice when it comes to forest fire suppression. One of the most popular modelling techniques is the cellular automaton CA, which has been used to replicate the intricate dynamics of fire propagation. Although CA models are most commonly used, local transition rules are defined using significant research on the physical background of wildfires. The authors make use of Extreme Learning Machine (ELM), a well-liked paradigm for data-driven learning, to avoid defining transition rules. The ELM modelling approach employs local historical training data to define the local evolution rules of fire spreading, allowing for the creation of a simple CA modelling approach that disregards complex theory and multiple physical parameters required by traditional models. Combining ELM with the standard forest fire CA framework presents a new approach to CA modelling. The effectiveness of this method was validated using data collected from five fires in the western United States. The obtained findings show that the ELM did a good job of forecasting the likelihood that each cell would ignite. The suggested modelling technique allows for a precise definition of how wind velocity affects fire spread patterns. The simulation's performance is accurate, as evidenced by the validation against actual fire behaviour data, and better results can be observed in comparison to earlier published reports.

Chetehouna et al. Chetehouna, Tabach, Bouazaoui and Gascoin (2015) explain and demonstrate an ANNs tool built with the intent of simulating metrics such as Flame Height, Flame Angle, and, most importantly, Rate of Spread (ROS) in beds of pinus pinaster needles. In order to generalise these three values so that they can provide valuable information even for wildfires not included in the database, the ANN was trained and validated accordingly in order to deduce its ideal architecture. For the model validation phase, an experimental dataset was used. The dataset was not meant to calibrate the proposed model, yet they showcased satisfying results for it nonetheless. The developed ANN was also compared to three different literature models, one of which was semi-empirical while the other two were physical. The proposed model's results fared very well against them. Finally, all the ANN models generated by the tool were compared to two other experimental datasets from literary works. In conclusion, the ANN tool showcased potential in regard to the evaluation of the three aforementioned metrics, ROS, Flame Height, and Flame Angle, through the use of information not imported into the database.

Although this paper revolves around the prediction of wildfires, Subramanian et al. Subramanian and Crowley (2017) also give additional attention to social and financial costs. The basis for the research was conducted using the following two algorithms: the Asynchronous Advantage Actor-Critic and Value Iteration. Out of those two, the former is a recent direct policy search approach that, through DL, performs policy representation and state-space approximation concurrently. The developed tool uses satellite images of a region in northern Alberta, Canada, as its source. The difficulty of modelling the actual dynamics of fire spread patterns makes this task stand out in a particular way, as it requires the use of computationally expensive physics-based models more often than not. Additionally, treating the fires as an agent spreading across landscapes in response to neighbourhood environmental parameters poses a challenge in and of itself. To handle it, the directions a fire could go towards it were classified as North, South, West, East, and not moving. The areas are represented by cells in the landscape, and rewards are given at the end of each epoch, depending on the accuracy of the model. In this paper, readers will find easily accessible satellite data from government agencies. The models were developed to train a wildfire spread policy in a specific region for a number of different time frames. They also test the transferability of the policies to data from another region. The results are promising and compare really well to intelligent system applications for wildfire prediction. However, the authors aim to research the more specific matter of fire spread location.

Khazkad et al. Khakzad (2019) acknowledge that the wildland-urban interfaces (WUIs), wildland-industrial interfaces (WIIs) and wildland base interfaces are embraced in one main sector, wildland-human interfaces. WII can be described as a district where a variety of industrial factories, such as oil and gas depots, are merged with or sited within wildland plant life. There hasn't been much research on WIIs because most previous studies and efforts in modelling and risk assessment of wildfire incidents at wildland-human interfaces have focused on wildlands or WUIs. Modelling and danger evaluation of wildfires in WIIs are crucial, as due to the factories' functioning closing down and to safety matters or restoration and replacement of damaged entities, the reduction of income could be significant, along with the possible destruction of the industrial stations. In particular, as far as oil and gas factories are concerned, the outcome of wildfires in WIIs can be disastrous. Due to the high temperature of the fire, storage containers of ignitable and explosive petroleum products, including crude oil, gasoline, diesel, kerosene, and propane, can be destroyed and assist in the fire's extension to other units and containers. For the elimination of this risk, the existence of buffer areas is vital, as they guarantee the safety of oil and gas plants from wildfire incidents and the wildlands from possible inflammations at the stations. The creation of a buffer zone is equivalent to the establishment of some form of plant-free zone between the factories and the forest plant life. As specialised fire outspread simulation and danger evaluation techniques in WIIs are limited, buffer areas are determined by estimation. In many cases, buffer zones are insufficient for controlling wildfires. A solution was created to tackle this problem through the integration of dynamic Bayesian network (DBN) and fire behaviour prediction models, allowing for the simulation of wildfire growth in wildland-urban interfaces (WIIs). To account for wind's impact on the direction of fire spread, the Canadian Fire Behavior Prediction (FBP) system was utilised to determine the frequency and intensity of fire expansion. The obtained information was then applied to determine the likelihood of fire spread between nodes in the DBN, allowing for the identification of the most likely fire path and associated probabilities. Simplifying assumptions were made by Khakzad et al. in their model development, such as assuming constant weather and fuel conditions, which may decrease the accuracy of the burn probabilities. This is compounded by the uncertainties present in the FBP system's ability to predict the frequency and intensity of fire spread. The fire forecasting model is intended to be a tool to assist land-use developers, firefighters, and facility owners in improving their risk management strategies by providing insight into the most likely path of the fire and burn probabilities. While there are limitations to the model, such as the simplifying assumptions and uncertainties in the FBP system, it is unique in its approach to simulating and evaluating the risk of wildfires in WIIs, where there is a lack of expansion models.

Palaiologou et al. Palaiologou, Kalabokidis, Day, Ager, Galatsidas and Papalampros (2022) developed a new approach for expanding the datasets required for wildfire simulations using open-access information. The system was specifically designed for the European and Mediterranean regions, and the authors tested it in Macedonia and Greece, which have high ignition densities and a large amount of forested land. The authors used fire simulation modelling to estimate community exposure and map `fire sheds` that define the area where wildfires can potentially transfer to communities. Additionally, the simulation outputs were used to map landscape metrics that reflect the spatial scale of fire size and wildfire exposure complexity while considering the geography of land tenures. These outcomes could have significant implications for landscape fuel management policies in Greece.

Through the use of a deep convolutional inverse graphics network dubbed DCIGN, Hodges et al. Hodges and Lattimer (2019) demonstrate an ML technique for estimating the time-resolved geographical evolution of conflagration events. It should be highlighted that a major driving force behind this research is the enormous computing expense of predicting wildfires across vast and diverse terrain. The DCIGN network underwent training on both simple and complex terrains of homogeneous landscapes and was also tested for its effectiveness in predicting wildfire spread. The model for these landscapes utilised Rothermel's model, specifically the ROS it provides. All data used in this research was generated through computational models and over 10,000 model predictions were made to achieve the goal of determining burn maps in 6-hour increments with a maximum of 24 hours after ignition. It was discovered that the computational cost of the DCIGN network is much lower than that of older models, and the results were deemed adequate, with mean precision, F-measure, Chan-Vese similarity, and sensitivity metrics of 0.97, 0.93, 0.93, and 0.92, respectively. Using earlier forecasts as input, the DCIGN network proved the potential to predict burn maps longer into the future than older methods. Additionally, adding noise to the DCIGN's input parameters did not impact its predictions in any major way.

Introducing the first supervised ML application for wildfire spread prediction: FireCast. Radke et al. Radke, Hessler and Ellsworth (2019) conducted this research intending to simplify the process of effectively mediating and predicting wildfire growth. FireCast is the result, and it combines Geographic Information Systems (GIS) with AI in order to predict potential wildfire spread. GIS provides us with generated and appropriate geospatial input variables, which are then used by an AI model in order to make classifications and if needed, predictions about a specified target. FireCast utilises supervised learning and geospatial inputs in a manner similar to weather data, satellite imagery, elevation data, or fire perimeters provided by firefighters working to suppress wildfires. It determines patterns correlated with fire spread in specified landscapes in order to predict wildfire spread. So far, FireCast has been trained and evaluated exclusively based on data from the Rocky Mountain region of the United States. However, its scaling potential is promising if the necessary datasets are provided for more regions. FireCast's results have been compared to the most common predictive modelling software available to firefighting squads currently and can aid in further containing wildfire damage.

6.2. Fuel Characterisation

When fires are lit, fuel particles ignite, and heat is transferred between them by conduction, radiation, and convection. Consequently, the properties of living and dead vegetative fuels, as well as their moisture content, biomass, and vertical and horizontal distribution, can have a significant impact on fire behaviour, such as fuel consumption, rate of spread, and severity. Understanding and accurately predicting fuel properties is crucial for fire behaviour models, such as the Canadian FBP System and the FIRETEC model. Studies have been conducted at two different scales to forecast fuel properties. Regression applications have been used to forecast easily quantifiable variables, such as the crown biomass of individual trees, using variables such as height and diameter (e.g., Cermak et al. 2015, "Estimating Forest Fuel Loads Using Terrestrial Laser Scanning"). On the other hand, classification applications have been utilised to map fuel type descriptors or fuel quantities on a landscape, utilising visual interpretation of air pictures and the interpretation of spectral features of remote sensing data Lasaponara and Lanorte (2007). Although only a few studies have used ML for wildfire fuel prediction, this field of research holds much potential for further exploration. For example, Zhao, Ma, Li and Zhang (2018) applied ML algorithms, such as RF and CNNs, to map fuel types and compare their performance to traditional classification methods Huo, Li, Zhang, Sun, Zhou and Gong (2021). The characteristics of fuels play a vital role in determining fire behaviour, and the accurate prediction of fuel properties is essential for effective fire management. Further research in this field, especially in the application of ML techniques, has the potential to significantly advance our understanding and ability to predict and manage wildfires.

Linn et al. Linn, Reisner, Coleman and SMITH (2002) showcase a new approach for landscape-wide wildfire prediction, a model dubbed FIRETEC, which couples wildlife and atmospheric behaviour based on the principles of energy, momentum and mass conservation. Developed in 1997, FIRETEC is used alongside a second model specialising in hydrodynamics, HIGRAD, in order to simulate conflagration phenomena through the use of a three-dimensional terrain-following finite volume grid. The combined effort of these modelling systems' ability to simulate wildfires is meant to be used for the examination of such phenomena and their behaviour. Five examples are presented using the developed method, all in idealised situations using realistic conditions. While the results produced in this research cannot be classified as a breakthrough, the end goal was achieved, and this new method of physics-based full-transport model utilisation marks the initial development of a new pathway towards landscape-scale wildfire modelling. In addition, the generated simulations are relatively simple to understand and can be used to isolate some of the physical relationships that affect the behaviour of the simulated wildfires.

Riano et al. Riaño, Ustin, Usero and Patricio (2005) developed a series of ANNs with the end goal of calculating and evaluating the Fuel Moisture Content (FMC) metric, which is one of the most vital sources behind the danger of wildfires. The developed ANNs calculated the aforementioned metric by estimating the two implicated variables: dry matter content (DM) and equivalent water thickness (EWT). For DM, the authors utilised the Leaf Optical Properties Experiment (LOPEX) database, for which the samples were split into 60% / 40% subsets to be employed for the models' learning and validation phases, respectively. Furthermore, due to water masking the DM absorption features of fresh samples, DM was calculated for both fresh and dry matter. While for the specified dataset, DM and EWT predictions on dry samples produced similar results to other methods, DM estimations on fresh samples via ANN ($r2 = 0.86$) showcased significantly improved results while utilising inversion of Radiative Transfer Models ($r2 = 0.38$).

In Lassen Volcanic National Park (LVNP), Pierce et al. Pierce, Farris and Taylor (2012) aimed to analyse forest fuel patterns, evaluate the efficiency of RF as a method for modelling plot-level canopy fuel loads, and pre-map the loads. Their goals were to determine the differences in surface and canopy fuel loads across LVNP based on topography and vegetation type, map surface and canopy fuels using RF regression and topographic characteristics with LandSat data, compare our canopy fuel maps with standard datasets, and predict fire behaviour using the surface and canopy fuel maps.

Riley et al. Riley, Grenfell, Finney and Crookston (2014) centre around the challenge of ascribing forest plots to a set of target landscape grids. The author presents a modified version of the RF method, developed specifically with this goal in mind. It produces a seamless grid of tree data at a given landscape level. The results of this newly modified RF method showcased high accuracy, as well as a strong relationship between the target gridded data and the ascribed plot data for certain important variables. Forest Height was calculated at 97%, while Forest Cover and Vegetation Group were at 86% and 84%, respectively. This high accuracy provided by the RF method's assets promises satisfying results for several applications, such as risk estimation for wildfires to terrestrial carbon resources or impact analysis from fuel treatments on fire sizes and landscape-level burn probability. The possibilities further increase due to RF being able to utilise both numerical and categorical variables.

Serrano et al. López Serrano, López-Sánchez, Álvarez González and García-Gutiérrez (2016) use a number of methods, namely Knn, RF, and SVM, to calculate aboveground forest biomass using remote sensing information. All of the previously described strategies are viable alternatives to the standard parametric MLR method. It should be noted that the AGB's accuracy estimations are not always a source of scepticism among researchers. This is due to a number of error types spread across different factors, such as field measurement, plot location, and the individual tree biomass equations. Additional errors were also caused by the radiometric and geometrical corrections of remotely sensed data. It should be noted that the three techniques vary in their levels of usability. SVM, in particular, is not easy for non-experts to apply. Furthermore, the parametrisation of these algorithms directly influences the performance of the generated models. After thoroughly examining the results of each model, the authors came to the conclusion that SCM is the most effective of the models, but due to the difficulty of applying parametrisation to it, it should be used mostly by experts. RF, on the other hand, whose accuracy is lower yet still passable, is easier for non-experts to utilise. Conclusions on kNNs in comparison to RF remain to be determined, however.

A methodology for mapping the types of fuel was demonstrated by Garcia et al. García, Riaño, Chuvieco, Salas and Danson (2011) using multispectral information and LiDAR. Adapted to the biological characteristics of the European Mediterranean basin, the authors of this research propose a two-phase classification for identifying the fuel classes of the Prometheus categorisation system. First, they mapped the major fuel classes, including trees, grass, and bushes, to the non-fuel classes. Consequently, using LiDAR and multispectral data, the Support Vector Machine (SVM) classification was applied, and the overall accuracy of the rating with a kappa coefficient of 0.9 was 92.8 percent. This method is intended to distinguish additional fuel kinds based on the vertical data of the LiDAR measurements. The total accuracy of the final fuel type rating is 88.24, with a kappa coefficient of 0.86. The study revealed that there is some confusion between fuel types; seven species prefer significant tree cover, introducing vertical continuity with understory vegetation, whereas five species prefer trees with less than 30 percent shrub cover, with some fields covered by Holm oak. Low LiDAR pulse infiltration meant that the understory vegetation was not accurately sampled.

Chirici et al. Chirici, Scotti, Montaghi, Barbati, Cartisano, Lopez, Marchetti, McRoberts, Olsson and Corona (2013) used Airborne Laser Scanning (ALS) data and an IRS LISS-III image to map forest fuel types in two areas in Sicily, Italy, covering a total of 652 km². They generated 16,761 plots using a stratified sampling scheme and classified the forest fuel types using predictors obtained from spectral signatures and ALS metrics. They developed and tested three non-parametric classification approaches to replace traditional parametric methods: (i) CART, (ii) RF CART bagging, and (iii) Stochastic Gradient Boosting (SGB) CART bagging/boosting. The SGB method was found to be the most effective, with an accuracy of 84%, and canopy cover was identified as the most relevant ALS metric. The study demonstrates that these models can aid in fire management and mapping fuel types. Effectively summarised are the properties of classification and regression trees, as well as the preprocessing operation, classification algorithms, and results.

6.3. Fire Susceptibility Mapping

Based on the spatial probability or density of fire occurrence, fire susceptibility mapping is a technique for identifying regions at a higher risk of suffering wildfires. Although "fire vulnerability" and "risk" have been used, "fire susceptibility" is the phrase most commonly used in the literature Li and Koo (2019). Fire susceptibility mapping can be carried out using various algorithms, such as MaxEnt, BRT, or RF. These algorithms can be trained using remotely sensed data or agency-reported fire data combined with a variety of explanatory variables related to the landscape, climate, structures, and anthropogenic factors. The goal of fire susceptibility mapping is to develop a spatial model that can predict the likelihood of a wildfire occurring in a particular area Kam, Balch and Spies (2016). One common approach for fire susceptibility mapping is using a presence-only framework, like MaxEnt, which is based on the presence of fires in a specific area. Another approach is using a presence-absence framework, like BRT or RF, which takes into account both the presence of fires and the absence of fires in an area. These frameworks are generally employed in various modelling approaches to identify the areas that are most at risk of wildfire occurrence Cochrane (2011). Fire susceptibility mapping can be a valuable tool for fire managers and land managers as it can help to identify areas that are at a higher risk of wildfire occurrence and prioritise resources for fire prevention and suppression efforts.

Amatulli et al. Amatulli and Camia (2007) recognise that researchers have used spatial and non-spatial non-parametric prediction models in the context of long-term fire risk assessment to elucidate complicated linkages among wildfire factors. The primary goal was to disprove the spatial stationarity assumption made by conventional regression techniques in the connection between the response variable and the predictors. The CART and Multivariate Adaptive Regression Splines (MARS) models were evaluated, and the authors' predictive abilities for local fire incidence were compared. The test was conducted in Italy's middle Arno River Basin, a region that is prone to fires. A fire prediction model was developed utilising 1621 ignition locations observed between 1997 and 2003 and the road network, topography characteristics, and demographic data. The models generated two rather comparable prediction maps. The CART model performs better in terms of prediction power, which can be inferred from the use of the two models for the prediction of fire occurrence within the context of long-term fire risk assessment. Additionally, it produces homogeneous fire risk management units that might be valuable in supporting wildfire planning initiatives. The MARS model, however, has the ability to create a smooth prediction surface. The two models used the default settings; therefore, evaluating other setup values led to greater results. Additionally, the findings were helpful in analysing how each independent variable behaved during the regression procedure. Previous research has supported the road variable's positive association when represented in terms of road density. The use of x and y variables can add spatial information to the models, but they must be properly used since unexpected outcomes might arise.

By evaluating multiple criteria and employing data mining techniques, including binary LR and ANN, Adab et al. Adab (2017) aim to estimate the optimum land fire danger map. Using the Receiver Operating Characteristic (ROC), the predicted accuracy of land fire danger models was summarised. The ANN model had a higher ROC curve (AUC 87%) than the binary LR model (AUC 81%), and it had superior sensitivity and specificity. Results from the ANN model indicated that factors connected to human activity strongly explained the variation in the frequency of land fires. In addition, the ANN method found annual precipitation and annual mean temperature in relation to the presence or absence of land fires as significant contributors to land fire risk. The link between annual precipitation and annual mean temperature may increase the risk of wildfires by creating extremely dry conditions. The results expanded the usefulness of the topographic wetness index, slope parameters, and land cover in predictive analysis of land fire risks, which appeared to be more accurate in predicting land fire dangers in the Golestan region of Iran. The variation in ignition patterns was mostly explained by the land cover, which also had a substantial effect on the frequency of ignitions. In this study, it was shown that human impacts (such as land clearing) are a reasonable proxy for land fires in the study region, although non-anthropogenic fires may be rare. To help forest managers assess their level of susceptibility and prepare for mitigation, the study's map of land fire threats may be used as a starting point. With Golestan Province being the most prone to fire in Iran, this research's evaluation of its land fire risks and mapping of those hazards serves as a pilot study for a more thorough investigation of land fire hazards throughout northeast Iran.

A fire hazard model was developed by Bisquert et al. Bisquert, Caselles, Sánchez-Tomás and Caselles (2012) using LR and ANNs. When combined with fire history data, remote sensing variables (EVI and LST) were used as input variables to track the state of the vegetation. The LR approach was used to analyse various combinations of input variables. The best variable combinations were incorporated into an ANN, and the outcomes from both strategies were compared and assessed. The 8-day LST with fire history data gathered over the course of a year was the best set of input parameters discovered. The LST was anticipated to have a significant role in the fire hazard since higher temperatures are associated with reduced moisture content, and these conditions make it easier for plants to catch fire. The ANN showed greater precision and accuracy than the LR. The neural network's findings were then classified into three categories of fire hazard, with 14% of fires occurring at the low level of danger, 25% occurring at the medium level, and 65% occurring at the high level. Finding fire hazard maps that make activities like prevention and extinction easier is made possible by classifying the fire danger levels.

Oliveira et al. Oliveira, Oehler, San-Miguel-Ayanz, Camia and Pereira (2012) recognise that the EUMed region has Europe's highest fire incidence rate. The spatial and temporal distribution of the area's fire density is uneven. The interaction between natural and artificial elements that influence the occurrence and spread of a fire has an effect on the probability of its occurrence. In this study, the probability of a fire was predicted using two distinct methods: MLR and RF. The findings obtained using these two approaches were compared, and this allowed for the assessment of the prospective applications of the RF method for fire occurrence modelling as well as the evaluation of non-linear correlations between the factors that were not taken into account by MLR. Additionally, both approaches prioritised the variables in terms of their relative importance to the models, making it possible to pinpoint the elements that were shared by both and amplifying their value for understanding fire density distribution. The two models produced different findings, with the RF model demonstrating better prediction accuracy than the LR model because of the presence of non-linear trends. The RF model significantly reduced spatial autocorrelation in model residuals. Despite these discrepancies, both models predicted that northern France, northern Italy, and northern Greece had low fire densities, but northwestern Iberia and southern Italy had high densities. In addition, it was feasible to discover major common characteristics that provided crucial insights into the causes influencing the occurrence of fires in this region during the fire season.

Vasconcelos et al. Vasconcelos, Silva, Tomé, Alvim and Pereira (2001) acknowledge that the human-induced ignition risk has been left out of the created fire danger models in a number of studies. Therefore, the authors suggest that it is possible to develop the requisite prediction power and quantify ignition likelihood in space by analysing historical data on the locations of fire ignition points. The investigation, which analyses the data included in the spatial features of the phenomena, is carried out by utilising inductive approaches in a raster GIS. A layer showing the locations of ignition events and a series of layers related to possibly explanatory factors are both included in the raster GIs database used in the investigation. By combining LR and genetic neural networks, this data set is analysed. The suggested model uses a number of independent variables and a binary event (presence or absence of ignition), making the LR acceptable because it has been effectively used in other research. Neural networks have been used in this investigation to see if non-linear, non-parametric approaches may outperform the outcomes from conventional statistical methods.

The Madrid region exemplifies the socioeconomic changes generated by the occurrence of forest fires in the European Mediterranean basin over the past several decades. Vilar et al. Vilar, Gómez, Martinez-Vega, Echavarría, Riaño and Martín (2016) explained wildfire occurrence by identifying these changes in socioeconomic variables as part of the migration from rural to urban areas by modelling the occurrence of wildfires over two distinct time periods. In the 2000s, predictors such as music, WUI, and roads were more meaningful despite a dramatic decline in FGI for both models. In the 2000s, both models performed better than their 1980s counterparts at detecting the occurrence of wildfires. The Maxent model outperformed the GLM in both time periods based on criteria such as sensitivity and commission error. A more consistent outcome ensures that the model may be replicated for further time periods, enabling the management of wildfires in this area through preventative measures. Assign extinction resources, for instance, in regions where there is a significant likelihood of extinction, especially where there is a high ecological value or socioeconomic vulnerability.

Two key concerns were the focus of Duane et al. Duane, Pique, Castellnou and Brotons (2015) : (1) Evaluate the predictive potential of classification of fire spread patterns using correlative models in a Mediterranean region affected by large fires. On the ground, fires were categorised based on their predominant pattern of spread, which is theorised to be influenced by weather, topography, and vegetation configurations (the fire behaviour triangle), (2) following this, an attempt was made to evaluate the relative contributions of these environmental elements to each form of fire spread pattern in order to test the hypothesis that each type of fire spread pattern is related with particular combinations of these components. Based on the dominant mechanisms of fire spread, convective flames are more closely linked to forest structural characteristics, while wind-driven fires are more closely associated with wind variables. In addition, topography-driven fires are anticipated to be affected by topographical characteristics and may occur in a broader range of contexts where other determinants of fire spread, such as high fuel loads or strong winds, have less influence. The reason for this is that strong winds or heavy vegetation can override the influence of topography, causing a fire that was initially driven by topography to become wind-driven or convective in nature. Therefore, topography-driven fires are more likely to occur in general circumstances where stronger driving forces are not dominant.

Bashari et al. Bashari (2016) showed that the BBN model can forecast wildfire incidence with a high degree of accuracy. This BBN model's ability to predict outcomes can be enhanced by including or removing other affecting variables. The process of upgrading the BBN model might be facilitated by conducting pertinent research to analyse the relationships between wildfire occurrence and various environmental and management parameters. Managers and policymakers may communicate more easily about the behaviour of systems because of the BBN model's graphical user interface. As a result, they may organise and arrange various sources of system knowledge, helping stakeholders make better decisions. The created fire risk assessment tool's primary goal is to give timely information about fire occurrences. It helps management avoid uncontrolled fire events or reduce risks, particularly in dry and semi-arid regions with potentially dire effects. BBN modelling technique offers managers a valuable tool to identify areas at the highest risk of fire outbreaks, and significantly improves the efficiency of current fire simulation models. BBNs can draw information for their probability tables from various sources, including data from other fire simulation models. The accuracy of a BBN model's probability tables is vital for determining its reliability, which may be determined by assessing the model's robustness - the degree to which deviations from the network's probability assessments impact the output. The robustness of the fire BBN model can be determined by sensitivity analysis. The established BBN model for predicting fire occurrences possesses two critically desirable qualities: the ability to predict and the ability to accommodate ambiguity.

The idea of the distinct temporal patterns of wildfires generated by people is the foundation of this study of Yago et al. Martín, Zúñiga-Antón and Mimbrero (2019). It is crucial to understand that time (month, day of the week, etc.) plays a crucial role in both the ignition likelihood overall and the variables influencing this probability. As human activities are influenced by daily, weekly, monthly, and seasonal cycles, this is based on the spatiotemporal aspects of human activities. This study's objective is to create seasonal and day-type models that take into consideration the varying spatiotemporal behaviour of human-related driving variables over the likelihood of wildfire igniting in northeast Spain. Ultimately, the goal of this effort is to create more effective dynamic predictive models by making forecasts that are more correct. Due to the dynamism of particular fire causes and the unique temporal unpredictability of human activity, a new analytical approach was developed. Innovative in design and execution, the suggested models are adapted to specific fire occurrence scenarios, leverage presence-only approaches (MaxEnt), and utilise high-resolution geographic datasets to track fire ignitions and human-related drivers of wildfires. To examine the effectiveness of these dynamic models, data from wildfires in 2012 were utilised, and their predictive capacity was compared to that of static models and random background samples. Overall, dynamic models outperform static techniques, routinely returning AUC values above 0.85 as opposed to the static models' 0.7 values.

Vacchiano et al. Vacchiano, Foderi, Berretti, Marchi and Motta (2018) provided evidence that, depending on the habitat and season, the fire regime in an alpine environment has various patterns and causes. The most frequent sources of fire ignition were anthropogenic drivers, for reasons connected to irresponsibility, while the frequency of fires started by lightning has been rising. From a management standpoint, the spatially explicit method enables the implementation of spatially targeted fire control tactics and may be incorporated into future regional and local fire management plans. Spatial risk assessments can benefit managers in the design of fuel management actions, the selection of watering sites for helicopters, the parameterisation of fire behaviour and landscape dynamic models, and the simulation of various fire scenarios and firefighting techniques. By integrating fire danger and fire susceptibility, a cell-by-cell assessment of the resulting fire risk is possible. To restore the historical disturbance regimes and improve the functionality of forest ecosystems that have developed with fire, less vulnerable regions may need to reevaluate the rigorous fire suppression strategy and allow fires to burn a small amount of the terrain. The relevance of urban areas and highways as potential ignition sources, rules governing development at the urban-wildland interface, and dangerous human behaviours near hotspots and during periods of high weather risk are all highlighted. To successfully lower the risk of wildfires, silvicultural prevention should be performed more regularly, with the aim of reducing the quantity and continuity of forest fuels under present climate change, drought, and lightning conditions.

Cao et al. Cao, Wang and Liu (2017) recognise that the RF-cost sensitivity analysis was the most accurate way of forecasting wildfire ignition susceptibility among the five models the scientists researched. The RF-cost sensitive analysis revealed the highest accuracy (88.47%) for all samples and accurately predicted the initiation of wildfires in Yunnan (94.23%). Compared to regularly employed GLM models (LR and probit regression models) and ANN, the RF-original model improved overall accuracy by 22.23%, 22.48%, and 9.56% percentage points, and wildfire ignition prediction by 16.63%, 16.03%, and 10.45% percentage points. Various methods, ranging from modern machine-learning models to conventional regressions, can be employed to evaluate wildfire vulnerability. Given that the vast majority of samples pertain to non-ignition, it is important to carefully process data samples to address concerns with data imbalance and avoid drawing potentially misleading conclusions. In order to achieve accurate ignition prediction, high sensitivity, as well as specificity and accuracy, must be taken into consideration. While the performance of machine-learning approaches (ANN and RF models) was superior to that of logistic and probit regressions, ideal results require additional research into the number of layers in the ANN and trees in the RF.

Parks et al. Parks, Holsinger, Panunto, Jolly, Dobrowski and Dillon (2018) acknowledge that wildland fire is a significant process affecting the western United States' forests. They investigated the causes of high-severity fires in forested ecoregions between 2002 and 2015, finding that live fuel was the primary factor (53.1%) in causing these fires, followed by fire weather (22.9%). Topography (10.3%) and climate (13.7%) had a smaller impact. They used satellite imagery to characterise live fuel and forecast the likelihood of high-severity fires in ecoregions where the model quality was deemed adequate. The framework and model projections may serve as a performance metric for land management agencies. This information is essential to managers entrusted with managing fuel and wildfires. Provided is an illustration of the projected likelihood of a severe fire occurring before and after fuel reduction procedures under moderate and extreme fire weather.

Ghorbanzadeh et al. Ghorbanzadeh, Valizadeh Kamran, Blaschke, Aryal, Naboureh, Einali and Bian (2019) emphasised the importance of generating wildfire susceptibility maps to aid emergency land management, wildfire prevention, response, and recovery. These maps guide the allocation of resources to minimise wildfire risk. However, the accuracy of the susceptibility maps generated by different methods can vary, making it essential to assess the effectiveness of each approach, especially those commonly used. The authors employed three distinct methods: ANN, SVM, and RF, which were trained on MODIS hotspots using a four-fold CV, and developed using data from previous wildfires between 2012 and 2017 and variables that influence them. To evaluate the methods' performance, the ROC curve was used, and a sensitivity analysis was conducted to assess the importance of each conditioning factor. Although there were differences in geographical predictions of wildfire susceptibility maps, the central, east, southern, and northern regions of the study area were identified as more vulnerable to wildfires. The accomplished workflow can be simply generalised and extended to multiple places, i.e., fire-prone regions, because the most pertinent wildfire conditioning elements and the most popular ML techniques were used. Examples of such locales include California, Australia, and Spain. Because of this, the workflow's transferability necessitates small adjustments and localisation of relevant conditioning factors.

Numerous nations have comprehensive forest fire protection plans that are built on firefighting and preventive strategies. One of the most essential components of preventing forest fires before they spread to broader areas is a fire detection system. Gigovic et al. Gigović, Pourghasemi, Drobnjak and Bai (2019) aimed to demonstrate the results of using an ensemble learning approach that utilises a Bayesian average of predictions from SVM and RF methods. They used ML algorithms to predict where forest fires are likely to occur and generate models to simulate these locations. The authors used supervised and flexible ML algorithms (SVM and RF) to compare forest fire susceptibility maps in Tara National Park, Serbia, as regional forest fire modelling is a common and complex problem that is difficult to assess and predict. All models produced scientifically acceptable results based on observed AUC and could be used to map forest fire vulnerability at a regional level. The outcomes showed that the ensemble model employing the Bayesian average performed better than the alternatives.

Pourtaghi et al. Pourtaghi, Pourghasemi, Aretano and Semeraro (2016) employed three ML/data mining techniques to map the susceptibility of forests to fires using a set of topographical, meteorological, and geological variables. The authors utilised the forest fire occurrence in Minudasht Township, Golestan Province, Iran, to develop and validate the differences between the ML models. The models BRT, GAM, and RF scored the best performance peaks with AUCs of 0.8084, 0.8770, and 0.7279, respectively, in identifying the absence or presence of a forest fire. To identify the factors that have the greatest impact on forest fires' spatial distribution, feature selection techniques were employed. According to the results of BRT, GAM, and RF, the most influential factors in determining the chance of forest fires are annual rainfall, slope degree, distance from roadways, land use, and annual temperature. This study reveals that the GAM model may be superior to the BRT and RF models for predicting and mapping forest fires. The results of this study can be utilised to distribute fire control resources, assign duties, and give early warnings. The findings are an important addition to the current research on forest fires, and the models can be enhanced by adjusting them to various forest types, tree compositions, and CC percentages. In general, the authors could not use the same variables across different locations due to the specific characteristics of forest fires in each area. However, the results of these models could be valuable not only in this field but also in other areas by comparing them with other data mining models such as CART, MARS, ANN, and SVM.

Tehrany et al. Tehrany, Jones, Shabani, Martínez-Álvarez and Bui (2019) introduced and verified the LogitBoost ensemble-based decision tree (LEDT) method, which combines the LogitBoost ensemble with a decision tree. The model was trained and validated using a GIS database including 257 fire locations and ten forest conditioning factors; it was then used to predict the susceptibility of pixels in the research area to two types of forest fire and non-forest fire. The experimental results reveal that the proposed model accurately identifies forest fire-prone areas, resulting in more reliable planning and prevention management. One key advantage of the LEDT over other ML approaches is that it does not require complex optimisation. To establish the optimal number of tree-based classifiers required to optimise the performance of the LEDT model in fire susceptibility mapping, a trial-and-error procedure is required. Unlike benchmarks such as RF, SVM, and KLR, the LEDT model prioritises processing incorrectly identified pixels by increasing their weights and decreasing the weights of correctly categorised pixels, leading to better performance with uncertain and noisy data. As a result, the LEDT model is more accurate and reliable for mapping forest fire vulnerability, making it a novel technique that can be applied to other geo-environmental problems. This research may assist other researchers in developing susceptibility maps for various regions.

Zhang et al. Zhang, Wang and Liu (2019) conducted a study in Yunnan Province, China to examine the spatial prediction of forest fire susceptibility using a deep architecture convolutional neural network (CNN). The researchers employed multicollinearity analysis and the IGR technique to retrieve historical forest fire locations between 2002 and 2010 and optimised a set of 14 parameters that influence forest fires. Additionally, they pre-processed techniques for generating effective training sample libraries and the forest fire-affecting parameters. To improve prediction accuracy, the study optimised hyper-parameters and constructed a CNN architecture appropriate for predicting forest fire susceptibility. To prevent overfitting, the CNN model included numerous conventional approaches, including an increase in training samples, regularisation, batch normalisation, and a simplification of the architecture. The generated model was then applied to the test dataset in order to build an ignition probability prediction map. Statistical metrics, including WSRT, ROC, and AUC, were used to compare the performance of the proposed model to that of established methods. The CNN model outperformed benchmark techniques based on the ROC-AUC evaluation, achieving an AUC of 0.86. The resulting probability map generated by the CNN model successfully distinguished the extremely high and very low sensitive zones, producing a distinct susceptibility spatial pattern. Furthermore, the CNN model demonstrated excellent generalisation capabilities and fast prediction times when utilising GPU-accelerated computing technologies.

6.4. Fire Perimeter and Severity Mapping

The management of fires requires the use of two distinct types of maps. The first category consists of exact maps of the active fire perimeter, which are required for daily evacuation and suppression planning, as well as modelling of fire expansion. The second type of map is that showing the final burn perimeter and fire intensity, which are essential for evaluating the economic and ecological repercussions of wildfires, predicting them, and planning for recovery. In the past, manual methods such as aerial, ground, aerial GPS, and other traverses were used to sketch map fire perimeters. However, these methods are time-consuming, labour-intensive, and can have a high degree of uncertainty Kennedy and McRoberts (2009). Since remote sensing was invented in the 1970s, identifying active fire areas has been the focus of research to develop methods for mapping fire perimeters and burn severity using remote sensing imagery. Techniques such as satellite and aerial imagery, thermal infrared, and lidar sensors are examples of remote sensing methods that can provide detailed and precise information on the location and size of active fires Li and Koo (2021). In addition, these technologies can be utilised to create maps of the final burn perimeter and evaluate the intensity of the fire. These maps are valuable for measuring the fire's economic and ecological impacts and for recovery planning Kennedy, Feddema and McRoberts (2013). The combination of techniques with remote sensing data has gained popularity in recent years for mapping fire perimeters and severity. This method allows for the automatic detection and classification of areas affected by fire in satellite and aerial imagery, resulting in a more efficient and precise mapping of fire perimeters and severity Szpakowski and Jensen (2019).

Lutes et al. Lutes, Keane, Caratti, Key, Benson, Sutherland and Gangi (2006) recognise that it is crucial to efficiently and proactively monitor and analyse the danger while also analysing the success or failure of a burn in order to adequately document wildfire effects, estimate the harm done to the whole ecosystem, and determine the short- and long-term affects it delivers on a region. The potential for future treatments and wildfire mitigation strategies as a whole is also expected to be evaluated and validated by relevant parties. Monitoring wildfire effects, however, is frequently difficult because data collection is a demanding task that necessitates significant funding, resources, and sampling expertise. In many instances, this latter factor is a major bottleneck when implementing wildfire monitoring because relevant agencies and stakeholders lack the standardised protocols to meet their specific goals. The "Fire Effects Monitoring and Inventory System" is a complete system that C. D. Lutes et al. developed in response to the aforementioned comments (FIREMON). The suggested platform is designed to meet the needs of fire control organisations with regard to monitoring and inventory for a variety of ecosystems, fuel typologies, and geographic regions (mainly focused on the United States). To enable stakeholders to efficiently monitor the effects of wildfires, the platform consists of standardised sampling techniques, databases, field forms, data analysis frameworks, and an image analysis guide. It also allows stakeholders to collect and store all sampled data, extract insightful information from it, summarise it, link it to satellite imagery, and map the sampled data across the target geography using image processing in a modular way.

K. R. Al-Rawi Al-Rawi, Casanova, Romo and Louakfaoui (2002) and colleagues conducted a detailed examination centred on researching a variety of wildfire occurrences in Valencia, Spain. Monitoring the spread of smoke and mapping the region impacted by the wildfire was done together with basic fire detection to track the incidence of fires. This research was conducted during the 1994 fire season. The researchers watched the spatiotemporal progression of the wildfires they were studying daily. Because burnt area mapping can identify the specific pixels that burn between two successive photos, it is determined that this methodology outperforms previous monitoring methods by a significant margin. Additionally, the authors developed a method that would overstate the extent of the fire by treating the pixels just below the flames as being on fire. These methodologies were benchmarked and documented. As a last point, it should be noted that a fire that manifests itself several times should be closely monitored since the pace at which wildfires spread exponentially increases with each succeeding occurrence of the fire. It is concluded that the proposed method is adequate for defining and monitoring the fire propagation map as well as the recently impacted region.

When evaluating the likelihood of burned scars from a single post-fire event, Pu et al. Pu and Gong (2004) discovered that the LR method is more effective than the NN algorithm, although both yield similar and acceptable results (with an overall average accuracy greater than 97% for both methods at the two study sites). They discovered that across all six original TM bands and five vegetation indices, the original TM4 and TM7, NDVI1 (TM4, TM7), and NDVI2 (TM4, TM3) are the most effective at distinguishing between burned and unburned regions. However, the prediction accuracy of samples gathered from shady and gloomy locales is lower than that of those acquired from regions directly exposed to sunshine. On the basis of the efficacy of the LR and NN in predicting burned scars using datasets extracted from a single post-fire Landsat 7 ETM image at the two study sites, these techniques can be used in similar areas, but more conventional techniques (such as linear discriminant analysis) should be considered first when perfect datasets are available before applying more potent techniques (e.g., LR and NN).

By using remote sensing pictures, Zammit et al. Zammit, Descombes and Zerubia (2006) hope to solve the issue of burned area mapping. In this case, only one after-fire satellite picture taken by the SPOT5 satellite served as the basis for the assessment of burnt land discrimination. SVM, a classification technique, was used to define charred regions. This suggested approach is contrasted with other well-known classifiers, such as the K-Nearest Neighbors or K-Means algorithms, which are frequently used in pattern recognition as benchmark classification techniques. The outcomes generated by the various classifiers are also contrasted with official burned area numbers that are gathered from real-world data.

Dragozi et al. Dragozi, Gitas, Stavrakoudis, Theocharis and San-Miguel-Ayanz (2011) aimed to address the issue of burnt area mapping by utilising a single post-fire Very High Resolution satellite image. In this study, the effectiveness of two classification methods, namely SVM and k-NN, in accurately mapping burnt regions was investigated. The results showed that both methods produced highly accurate burnt area maps. However, the SVM classifier was found to have slightly higher overall classification accuracy than the k-NN classifier. Additionally, SVM demonstrated superior performance in classifying various classes. The primary limitation of the current object-oriented SVM method is its difficulty in being used as an operational tool for burnt area mapping, as it cannot be implemented in a single software interface.

Pereira et al. Pereira, Pereira, Libonati, Oom, Setzer, Morelli, Machado-Silva and De Carvalho (2017) used PROBA-V imagery and VIIRS active fire data to automatically extract multispectral samples and train a One-Class SVM for burnt area mapping. This strategy was applied to the Cerrado savanna in Brazil by combining surface reflectance and active fire data on a biweekly basis. The suggested method was evaluated using Landsat-derived reference maps and compared to the Collection 6 MODIS Burned Area product (MCD64A1). In comparison to MCD64A1, the algorithm enhanced the recognition of tiny scars and gave more precise findings. This approach can also detect and map burn scars in the absence of current fires, removing potential sources of error.

6.5. Fire Detection

The key to enabling a prompt and efficient response to wildfires is the timely detection and identification of the fire before it grows out of control. Traditional methods of wildfire identification, such as using human observers to detect smoke from fire towers, aircraft, or the ground, have several limitations. Automating the detection of heat signatures or smoke in infrared or optical photographs can circumvent several limitations, such as limited coverage, human error, smoke from nearby fires, and limited daylight hours. This automation can improve the spatial and temporal coverage of detection, boost its effectiveness in hazy environments, and reduce human observation-related bias Al-Rawabdeh and Ahmed (2019). AI techniques can be used to classify and identify heat signatures and smoke in images, providing a more efficient and accurate method of wildfire detection. These techniques can be used in combination with traditional methods of detection, such as human observation, to increase the overall effectiveness of wildfire detection Koo and Li (2020). The use of automated systems for wildfire detection can also provide valuable data for fire management and resource allocation. By providing real-time information on the location and size of fires, automated systems can help fire managers make more informed decisions on resource allocation and firefighting strategies. This can ultimately lead to more effective and efficient wildfire management Perona and Radeva (2019).

Arrue et al. Arrue, Ollero and Martinez-de Dios (2000) recognise forest fires as a significant cause of environmental disasters that threaten human life and cause economic and ecological harm. Traditional human surveillance for forest-fire detection is subjective and unreliable, leading to an increasing interest in automatic surveillance systems. To address the problem of false alarms, the authors propose the False Alarm Reduction (FAR) system, which utilises artificial neural networks (ANNs) and infrared and visual cameras, meteorological sensors, and geographic information to create a decision function. The system also includes new software tools to validate alarms for human operators. The FAR system takes advantage of information redundancy from the cameras and develops a fuzzy expert rule base for decision-making.

Sayad et al. Sayad, Mousannif and Al Moatassime (2019) offer a strategy that uses big data and remote sensing to generate a dataset for data mining algorithms to assess and predict the occurrence of wildfires. Using data from the MODIS sensor on both the Terra and Aqua satellites, the technique consists of seven phases, from data collection to data extraction. The sensor was chosen because it delivers several data products and covers the entire planet, making the model worldwide applicable. In this work, an experiment was undertaken to examine the dataset created to forecast the chance of wildfires in a specific area of Canada's forests using the two well-known data mining techniques, ANN and SVM, on the "Databricks" big data platform. Using cross-validation, regularisation, classification metrics, and comparisons with other wildfire model data, the outcomes demonstrate great FOP accuracy for both approaches.

Liu et al. Yongsheng, Liu, Yansong, Yang, Chang, Yu and Gu (2015) developed a forest fire detection system that employs a wireless sensor network and an ANN algorithm to lessen the hazard of forest fires by delivering accurate fire alarms at minimal maintenance costs. Several forest fire factors are incorporated into the system's novel multicriteria detection to improve its accuracy. An ANN algorithm is utilised to incorporate sensor data corresponding to these characteristics into an alarm determination. The authors constructed a prototype of the proposed system consisting of a solar battery module, a fire detection module, and a user interface module to power sensor nodes in areas of the forest with sporadic sunlight.

Barboutis et al. Barmpoutis, Dimitropoulos, Kaza and Grammalidis (2019) recognise that false alarm rates are frequently high as a result of the similarities between flames and natural things, the wide range of flame appearances, and environmental changes like clouds, sunlight, and light reflections that make it more difficult to identify fires. Due to the chaotic and complex nature of fire occurrences, detecting fire from digital images is tough. To solve this difficulty, the authors merged a potent DL algorithm with multi-dimensional texture analysis utilising linear dynamical systems (LDS) in order to detect early fires from photographs. In this method, candidate fire areas of each image were retrieved using a faster R-CNN network, represented as a point cloud on the Grassmann manifold, and a VLAD descriptor was produced for each image. Photographs from two distinct databases containing several images of wildfires were used to assess the effectiveness of the suggested technique. These images included images of items that mostly had fire-like colours or colours similar to fire. In particular, photographs of annotated wildfires from the Corsican Fire Database (CFDB) and pictures of various objects and classes from the PASCAL Visual Object Classes dataset were utilised.

Due to the scarcity of real smoke photos for training deep models, Zhang et al. xing Zhang, hua Lin, ming Zhang, Xu and jun Wang (2018) utilised a quicker R-CNN to detect forest smoke using synthetic images generated by merging two forms of smoke (real and simulated) against a forest background. Using photos of actual forest smoke, the results of an experiment demonstrated the efficacy of this method, which not only addresses the problem of a lack of data but also eliminates the requirement for sample labelling. Despite the unnatural aspect of the synthetic photos made by adding simulated smoke to a forest background, this method surpassed the other methods for creating smoke.

Li et al. Li, Chen, Wu and Liu (2020b) aim to assist in the creation of a system that continuously monitors vast regions of forested and hilly terrain. In the end, the authors suggest a framework that may operate in a natural setting and quickly identify smoke during a wildfire. The suggested wildfire detection system's detection sensitivity and attaining low false positive rates are the main goals of this study since it is crucial to reduce the severe impact of wildfires. The authors suggest a 3D parallel fully convolutional network (3D-PFCN) leveraging pyramid categorisation as a result, in order to satisfy the aforementioned objectives. The central component of the proposed 3D classification framework is a pixel-level segmentation neural network, which can extract a number of spatiotemporal characteristics and enable classification using a pyramid structure. Using a comparable environmental picture to that used in training data, which corresponds to a very complex natural environment, the suggested classification framework was able to detect the presence of smoke accurately and quickly in real-world tests.

Cao et al. Cao, Yang, Tang and Lu (2019) propose an ABi-LSTM technique for detecting early forest smoke. The proposed method includes three parts: (1) spatial feature extraction using an Inception V3 network, (2) temporal feature extraction using a BiLSTM model, and (3) classification optimisation using an attention network with a soft attention mechanism. The suggested ABi-LSTM approach outperforms existing methods in detecting early forest fire smoke, according to extensive testing data. An ablation study was also conducted to evaluate the performance of each submodel in the ABi-LSTM. The attention mechanism, which can adaptively focus on discriminative frames, has a significant impact on the proposed ABi-LSTM and may be suitable for early forest fire smoke detection.

Alexandov's et al. Alexandrov, Pertseva, Berman, Pantiukhin and Kapitonov (2019) primary objective was to compare techniques used for wildfire monitoring activities. Their research concentrates on ML and DL Methods because AI techniques can be better applied to real-time monitoring jobs. The study clearly established the benefits of ML approaches compared to traditional image-processing techniques used for monitoring. The study takes into account traditional and DL techniques such as YOLO, Faster R-CNN, SSD, and cascades of Haar and LBP. The authors also compared different approaches to wildfire aerial detection. The performance and accuracy of the detection were the comparison criteria used in their methodology. The study shows that traditional techniques provide the highest performance, but their accuracy is inferior to that of Faster R-CNN and YOLO models. The SSD model demonstrated the poorest performance results and accuracy results comparable to those of traditional techniques. Application of Faster R-CNN for smoke detection resulted in a 4 FPS average performance and detection only of smoke with a light colour shade. Among all the models taken into consideration, the YOLO model performed with the greatest accuracy and was the quickest among DL models. YOLO is more suited for early fire detection, similar to Faster R-CNN. As a result, this model is considered better for fire monitoring problems.

Phan et al. Phan and Nguyen (2019) recognise that to monitor and stop fire dangers from becoming disasters, the authors want to create an autonomous and intelligent system based on imaging data streams that are accessible via constantly operating satellites. Satellite data, however, presents particular difficulties for image processing methods, such as temporal correlations between time steps, the complexity of spectral channels, and antagonistic circumstances like cloud and light. The scientists introduced a unique approach for detecting wildfires at the pixel level that makes use of satellite pictures and advanced deep-learning architecture. Specialists in wildfire mitigation can thoroughly analyse areas of interest on a map of the world using the detection outputs that are further shown in an interactive dashboard. The GOES-16 streaming data source is used to build and test the suggested system. Empirical analyses demonstrate this approach's higher performance compared to baselines with a 94% F1- score, 1.5 times quicker detections, and resilience against various wildfire kinds and adversarial situations.

Ba et al. Ba, Chen, Yuan, Song and Lo (2019) recognise the benefits of satellite remote sensing in environmental studies, particularly in the detection and monitoring of wildfires through smoke detection. However, existing techniques are limited in their ability to discriminate smoke from a small number of classes. To address this, the authors proposed USTC SmokeRS, a benchmark for large-scale satellite imagery smoke detection consisting of six classes and spanning various geographic locations. Additionally, they created SmokeNet, a unique CNN model with spatial and channel-wise attention that surpasses previous techniques in terms of accuracy and Kappa coefficient, even when trained with a small number of images. The SmokeNet model trained with 64% of the training images achieves an accuracy of 92.75% and a Kappa coefficient of 0.9130, whereas the model trained with only 16% of the training images improves the classification accuracy and Kappa coefficient by at least 4.99% and 0.06, respectively, compared to previous methods.

A UAV equipped with GPS was used by Zhao et al. Zhao et al. (2018) to create a high-resolution map of a given region. The primary challenge in classifying wildfire images to date has been the lack of standardised identifying markings. The fire aspects of colour, shape, texture (smoke, flame, or both), and background can vary greatly from scene to scene. The scientists demonstrated the efficiency of employing deep CNNs with saliency detection to locate and identify wildfires in aerial pictures. To identify the primary fire regions and separate fire regions from many fire photos, the saliency detection method is used. The saliency detection technique is used to identify the primary fire zones and separate them from other fire pictures. The suggested method prevented significant feature loss brought on by direct downsising. Additionally, the database's volume was greatly increased by this method. In this study, the "Fire Net" DCNN architecture was used. The classification results were satisfactory. By obtaining a 98% overall accuracy, the suggested architecture's performance was better than earlier approaches. Additionally, "Fire Net" was able to detect wildfires in real-time with an average processing speed of 41.5 milliseconds per image. Fire Net was tested on 40 randomly selected photographs from news stories on wildfires to demonstrate its usefulness, and it correctly identified every single one of them.

Forests play a crucial role in maintaining the balance of our planet's ecology, but forest fires often go undetected until they have spread significantly, making them difficult to control and suppress. These fires can be caused by various factors such as human error or natural causes and can result in devastating damage to the environment and atmosphere. They contribute to 30% of the CO_2 in the atmosphere and emit large amounts of smoke. In the long term, forest fires can alter regional weather patterns, worsen global warming, and lead to the extinction of rare plant and animal species. To prevent the impact of forest fires, authorities use early detection and monitoring systems, such as observers, aerial monitoring, and sensors, to identify and contain fires in their earliest stages. Fire spread behaviour prediction is also important in fire management, as it helps reduce the deployment of suppression resources and improves evacuation planning. Fuel characterisation also influences fire behaviour, and the use of regression or classification applications and techniques has the potential to improve fire management.

The following table provides a comprehensive overview of various Wildfire Detection and Response Models, focusing specifically on models for fire spread behaviour prediction, fuel characterisation, fire susceptibility mapping, fire perimeter and severity mapping, and fire detection. The table characterises these models based on different factors and categories such as weather characteristics, fire and smoke detection methods, environmental management practices, fuel consumption, fire spread rate, and the methods used to predict and respond to wildfires. This table serves as a valuable resource for individuals and organisations involved in wildfire management, providing a clear understanding of the various approaches used to detect and respond to wildfires, and the factors that influence their effectiveness.

Table 2: Summary of Detection and Response Models

References	Weather Characteristics	Fire & Smoke Detection Method	Environmental Management	Fuel Consumption	Fire Spread Rate	Method
Liu et al. Yongsheng et al. (2015)	Not applicable	A forest fire detection system comprising a wireless sensor network with an ANN algorithm.	The MODIS data products were obtained from the online Data Pool with permission from the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center.	Not applicable	Not applicable	The ANN algorithm provides support for multi-criteria detection.
Zhao et al.Zhao et al. (2018)	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	The dynamic SVM classifier is applied to continuous video frames containing dynamic characteristics.
Barboutis et al. Barmpoutis et al. (2019)	Not applicable	Combining the capability of contemporary DL networks with multidimensional texture analysis based on higher-order LDS, a novel image-based fire detection method is proposed.	the European Environment Agency	Not applicable	Not applicable	Faster Regions with Convolutional Neural Networks (R-CNN) and spatial texture analysis (Grassmannian VLAD encoding)
Zhang et al. xing Zhang et al. (2018)	Not applicable	Faster R-CNN was used to detect smoke in forest.	Not applicable	Not applicable	Not applicable	Faster R-CNN was used to detect smoke in the forest.
Li et al.Li et al. (2020b)	Not applicable	3D-PFCN for wildfire smoke detection	Not applicable	Not applicable	Not applicable	A pyramid classification and a parallel structure of 3D convolution and 3D pooling
Cao et al.Cao et al. (2019)	Not applicable	Early forest fire smoke detection.	Not applicable	Not applicable	Not applicable	An attention-enhanced bidirectional LSTM network (ABi-LSTM) for early forest smoke recognition.
Alexandrov et al. Alexandrov et al. (2019)	Not applicable	Artificial intelligence intended for detecting wildfires using unmanned aerial vehicles (UAVs).	UAVs environmental monitoring	Not applicable	Not applicable	Classical methods of ML and DL methods such as Haar and LBP cascades, Faster R-CNN, Single Shot Detector (SSD), and YOLO (You Only Look Once).
Phan et al. Phan and Nguyen (2019)	Weather information	A system for autonomous and intelligent wildfire detection.	Geostationary Operational Environmental Satellites (GOES-16) streaming data source.	Not applicable	Consider the spatial context of a specific pixel, such as its neighbouring pixels, because wildfires spread via nearby sites.	A innovative method for detecting wildfires that uses satellite imagery and an advanced DL architecture to locate wildfires on a pixel-by-pixel basis.

Ba et al. Ba et al. (2019)	Not applicable	USTC SmokeRS is a new standard for large-scale satellite imaging smoke detection based on MODIS data.	The Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center at the Goddard Space Flight Center in Greenbelt, Maryland, United States of America	Not applicable	The model for distinguishing between smoke pixels and spreading regions in a picture.	A new CNN-based approach for satellite remote sensing to detect smoke situations.
Zhao et al. Zhao et al. (2018)	Not applicable	The method of saliency detection is used to discover core fire areas and extract fire regions from several fire photos.	Envisat satellite image of wildfire	Not applicable	Not applicable	Saliency detection and a deep convolutional neural network for fire identification and localisation in aerial pictures.
Linn et al. Linn et al. (2002)	Conditions meteorologically present during the Oso complex fire.	Not applicable	Not applicable	Conditions of fuel availability during the Oso complex fire.	The rate of fire spread will be computed using BEHAVE.	Using a terrain-following three-dimensional finite volume grid, FIRETEC is integrated with the hydrodynamics model HIGRAD to simulate wildfires.
Riaño et al. Riaño et al. (2005)	Not applicable	Not applicable	Not applicable	Using neural networks and the LOPEX database to estimate FMC.	Not applicable	ANN were tested to estimate FMC
Pierce et al. Pierce et al. (2012)	To derive fire weather parameters using Fire Family Plus	Not applicable	The climate is Mediterranean, with summers that are warm and dry and winters that are cold and damp.	Canopy Bulk Density, Canopy Cover, Canopy Base Height, and canopy Height were mapped for the Bluff (2004) fire using 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 dataset.	RF will model and map forest canopy fuels for analysis of fire behaviour in LVNP, California, United States.
Riley et al. Riley et al. (2014)	Not applicable	Not applicable	Not applicable	On 30m grids, the Landfire project provides more than 20 national geospatial layers, including topography, fuel, and vegetation layers.	Not applicable	A modified RF method for assigning forest plots to a series of landscape grid targets.
López-Serrano et al. López Serrano et al. (2016)	Not applicable	Not applicable	The Sierra Madre Occidental is located in the northern portion of the Mexican state of Durango and encompasses an area of 1,142,916 acres.	The United Nations Framework Convention on Climate Change (UNFCCC), which identifies AGB as a Key Climate Variable, is a global treaty on climate change.	Not applicable	Utilising remote sensing, the k-Nearest Neighbors (k-NN), RF, and SVM ML algorithms are used to calculate aboveground forest biomass. datasets

García et al. García et al. (2011)	Not applicable	Light Detection and Ranging (LiDAR) data	The Natural Environment Research Council of the United Kingdom (Airborne Remote Sensing Facility 2006 Mediterranean Campaign, grant WM06-04)	It has been established that multispectral data may be utilised to map fuel kinds.	Not applicable	A SVM classification combining LiDAR and multispectral data.
Vilar et al. Vilar et al. (2016)	Not applicable	Not applicable	Not applicable	Not applicable	The expansion of WUI caused by urbanisation	ML Maximum Entropy models and GLM
Duane et al. Duane et al. (2015)	Not applicable	Not applicable	Mediterranean landscapes	Not applicable	Not applicable	ML Maximum Entropy
Adab et al. Adab (2017)	MODIS weather data	MODIS data were utilised for fire surveillance.	MODIS	MODIS FMC data	Not applicable	Built land fire hazard maps using BLR and ANN techniques
Bisquert et al. Bisquert et al. (2012)	MODIS land surface temperature data	MODIS fire monitoring data	MODIS environmental data	MODIS FMC data	Not applicable	LR and ANN
Oliveira et al. Oliveira et al. (2012)	Not applicable	Not applicable	Mediterranean area data	Not applicable	Corine Land Cover and point survey data	MLR and RF
Vasconcelos et al. Vasconcelos et al. (2001)	Not applicable	Several Forest Service field crews collect information on the areas of fire occurrences.	Not applicable	Not applicable	Arson data	LR and ANN
Yago et al. Martín et al. (2019)	MODIS FWI data	Not applicable	Mediterranean region	MODIS fuel data	Not applicable	Maximum Entropy algorithm
Vacchiano et al. Vacchiano et al. (2018)	Mean annual temperature	Not applicable	Osta Valley region in northwest Italy	Not applicable	Education and neglect prevention throughout the cold months.	Maximum Entropy algorithm
Markuzon and Kolitz Markuzon and Kolitz (2009)	Landsat land cover data and National Oceanic and Atmospheric Administration (NOAA) weather observations	Fire monitoring were performed using data from the MODIS	Land cover information collected by Landsat Thematic Mapper satellite.	Land cover information obtained by the Landsat Thematic Mapper satellite is used as a surrogate for data on flammable material.	Not applicable	Utilising data mining techniques to create fire prediction models. k-NN, RF, DT, and BNs.
Artés et al. Artés et al. (2016)	Not applicable	Not applicable	Not applicable	Dead fuel moisture, live fuels moisture	Wind speed and wind direction, among others, are used for real-time forest fire spread predictions.	FARSITE simulation engine with a Time-Aware Classification
Houssami et al. El Houssami et al. (2018)	Not applicable	Not applicable	Not applicable	Experiments were carried out by burning pine needle beds and WUI	A multiphase formulation that permits ROS to be used as a fuel	Submodels used to finish CFD models, especially when using a multiphase approach for wildfires.

Ascoli et al. Ascoli et al. (2015)	Days since last rain, air temperature and humidity, and wind speed	Not applicable	The entire dataset of ROS observations and environmental conditions during fire experiments is available on Comprehensive R Archive Network2 as example data (firexp) in the Rothermel R package.	Fuel models for litter, grass and shrub fuels	The Rothermel fire spread model.	GA in the Rothermel fire spread model.
Kozik et al. Kozik et al. (2014)	Not applicable	Not applicable	Geoinformation system such as Google Maps	The factors of the ambient medium, such as the kind of forest, the relative humidity, the amount of combustible material, and the thickness of the combustible material layer.	The wind velocity and direction, calculation of the wind chart based on relief data, and visualisation of fire evolution	Adaptive Prediction of Forest Fire Evolution Based on Recurrent Neural Networks
Zheng et al. Zheng et al. (2017)	The RAWS USAClimate 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 extracted from the LANDFIRE program's 2001 version product.	Forest fire spread simulating model	Simulation of forest fire propagation using CA and an extreme learning machine
Denham et al Denham and Laneri (2018)	Not applicable	Not applicable	Global environmental change conditions	Vegetation fuel type	Analysis of fire spread based on maps of burned regions without knowledge of the origin or spread of fires.	GA
Chetehouna et al. Chetehouna et al. (2015)	Not applicable	Not applicable	Not applicable	FMC and a P. pinaster fuel bed	This model estimates the flame height, flame angle, and rate of reactive oxygen species (ROS) of a bed of P. pinaster needles.	ANN
Subramanian and Crowley Subramanian and Crowley (2017)	The temperature is determined by processing satellite thermal pictures.	Not applicable	The USGS Earth Explorer data portal	Not applicable	The Bellman Equation	MDP, Asynchronous Advantage Actor-Critic and RL to augment physics-based forest wildfire simulations
Khakzad et al. Khakzad (2019)	Conditions relating to the weather, such as temperature, relative humidity, and wind speed	Not applicable	WUIs and WIIs	Burning index, fire potential index, drought index, and thousand-hour fuel moisture are examples of parameters.	A BN for modelling the spread of fire	DBN and FBP models to simulate the spread of wildfires in WIIs.

Arrue et al. Arrue et al. (2000)	Information from weather sensors and a database of geographic information.	A sensor interface, an image-processing tool, and a decision function constitute the FAR system.	Andalusia's Regional Environment Agency's Forest Fire Prevention and Restoration Service	Information from topographic, fuel, and use maps	Not applicable	The FAR system employs innovative IR-image processing algorithms and artificial neural networks.
Sayad et al.Sayad et al. (2019)	The Canadian Wildland Fire Information System provided the collected data (CWFIS)	The MODIS LST products are stored as files in the Hierarchical Data Format Earth Observing System format.	The NDVI, which is a vegetation index that shows the level of crop health, and the Canadian Forest FWI System are examples of crop health indicators.	The NDVI, which is a vegetation index, reveals the crop's level of health.	The CWFIS, The Canadian Forest Fire Behaviour Prediction (FBP) System	Neural Networks and SVM
Palaiologou et al. Palaiologou et al. (2022)	GIS weather data	Not applicable	GIS topological data	GIS fuel data	Monte Carlo simulations of fire propagation using the Minimum Travel Time technique	Minimum Travel Time fire spread algorithm.
Hodges et al. Hodges and Lattimer (2019)	Not applicable	Not applicable	Not applicable	Rothermel fuel model	Rothermel and FARSITE	Wildland-Urban Interface Fire Dynamics Simulator using DCIGN
Radke et al. Radke et al. (2019)	GIS weather data	Not applicable	GIS topological data	GIS fuels data	The FARSITE model	FireCast, a novel solution that combines AI and GIS
Amatulli, and Camia Amatulli and Camia (2007)	Meteorological data were gathered from the European Centre for Medium-Range Weather Forecast's 40-Year Re-analysis Data Archive.	Not applicable	Climate change in the EU-Mediterranean nations	A rating of fire risk based on fuel moisture	Fire spread- ISI	MLR, RF, MARS

7. Wildfire Restoration and Adaptation Models

The kind and state of the forest, as well as the intensity of the burn, directly influence the post-fire state of a burned landscape. Burn severity is a term used by fire ecologists to describe how a fire has affected the soil and the hydrologic system. In general, the effects on soil and its capacity to absorb and process water are more severe the denser the pre-fire vegetation is and the longer the fire burns on a specific location. High-intensity wildfires can lead to the complete elimination of all forest vegetation, including trees, shrubs, grasses, dropped needles, decomposing roots, and other ground cover or duff components that shield forest soils. This has a significant impact on the post-fire state of the landscape and can lead to a variety of negative consequences De Graff (2014). One of the major impacts of high-intensity wildfires is the development of a waxy, water-repellent layer on certain types of soil. This layer, known as hydrophobic soil, prevents water from reaching the soil and greatly increases the rate of runoff. This can lead to a variety of problems, such as increased soil erosion and flooding during storm events. Forested slopes are particularly prone to extensive soil erosion and floods following a wildfire, as the loss of vital surface vegetation leaves the soil exposed and vulnerable Moreno, Elías and Moreno (2002). The health, safety, and integrity of communities and natural resources further downstream are also at risk as a result of these concerns. For example, increased runoff and soil erosion can lead to downstream flooding, which can damage homes, businesses, and infrastructure. It can also lead to the loss of aquatic habitats and other natural resources Grant and Beschta (1996).

To mitigate these impacts and help restore the forest, various post-fire restoration techniques can be employed. One such technique is the planting of vegetation, including trees, shrubs, and grasses, which helps to stabilise the soil and reduce the risk of erosion. These efforts can be further supported by the implementation of appropriate land management practices, such as reducing the frequency of human-caused fires, limiting the extent of grazing and other human activities, and preserving remaining forested areas Reddy (Unknown). In addition, the restoration of natural hydrological systems is also critical to maintaining the health and integrity of the forest. This can involve the re-introduction of native species of vegetation, the creation of water retention features such as wetlands, and the restoration of streams and other waterways. These efforts can help to mitigate the risk of flooding, erosion, and other negative impacts, and promote the overall health of the forest and its associated ecosystems Fischer (Unknown). Due to the expected rise in frequency and intensity of wildfires caused by climate change, it is becoming more crucial to create effective fire-resistant landscapes. This may involve implementing measures such as using fire-resistant materials and plants, creating firebreaks, and promoting post-fire recovery. Collaboration between researchers, land managers, and local communities can help to ensure the long-term health and resilience of burned landscapes Stephens (2015).

As a result, the restoration and adaptation models are examined in this subsection. The different models are organised based on three primary sub-categories: (a) Climate Change, (b) Soil Erosion and Deposits, and (c) Smoke Particulate Levels, as shown in Fig. 4 Sub-categories of Restoration and Adaptation Models. These models aim to address the negative consequences of wildfire and to help restore the health and integrity of the forest and the surrounding landscape.

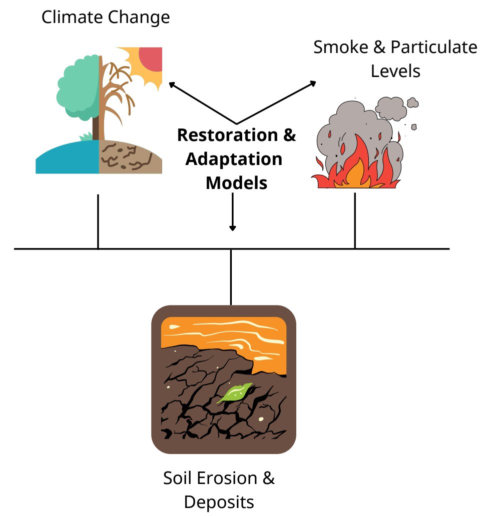

Figure 5: Restoration and Adaptation Models

7.1. Climate Change

One of the major global challenges facing us is climate change, which affects ecosystems, biodiversity, and human communities. In climate change science, transfer modelling is a popular approach to applying models developed for one study region to other locations. These techniques are becoming more prevalent for estimating climate change-related quantities. However, it is crucial to consider the transferability of the model when using machine learning for transfer modelling. Research in species distribution modelling has indicated that machine learning (ML) methods could be suitable for transfer modelling under future climate scenarios. ML techniques have demonstrated their capability to make precise predictions in various domains, making them ideal for extrapolation, a critical task in transfer modelling. However, it is crucial to be aware of the limitations and possible biases of ML models and thoroughly assess their performance before implementing them in new contexts. Several studies have demonstrated the potential of ML techniques for climate change modelling and transfer modelling. For example, Lu et al. Lu, Wei, Kim and Ding (2021) applied ML techniques to model species distributions under future climate change scenarios and found that their approach outperformed traditional statistical models. In a similar vein, Li et al. Li, Chown and Strand (2020a) employed machine learning (ML) techniques to simulate the effects of climate change on forest fires, and their findings revealed that their methodology could forecast variations in the extent and severity of fires with precision. In general, ML techniques could play a significant role in comprehending and alleviating the consequences of climate change. Nonetheless, it is critical to thoroughly assess and validate these models to confirm their reliability and accuracy in distinct settings.

Amatulli et al. Amatulli, Camia and San-Miguel-Ayanz (2013) acknowledge the increasing attention paid to the effects of climate change on forest fires at both the continental and local levels. As extreme fire scenarios are heavily influenced by weather, it is crucial to assess the rise in fire hazards and the subsequent impact of forest fires under climate change. The authors estimated burnt areas in the European Mediterranean (EU-Med) nations under previous and anticipated climatic conditions using the Canadian FWI to simulate historical monthly burnt areas (1985-2004) in EU-Med nations. They utilised three modelling techniques and found that MARS outperformed the others. Regression equations and substantial coefficients of determination were produced, even though variations across countries were noticeable. The MARS models were used to predict burnt areas for each nation and the EU-Med region under both IPCC SRES scenarios of the PRUDENCE project's HIRHAM's runs. In the EU-Med region, the models' results indicated a projected 66% and 140% increase in the total burnt area under the two scenarios.

Parks et al. Parks et al. (2018) note that North American fire regime features are expected to change in the next few decades due to human-induced climate change. In the context of a changing climate, a number of aspects of fire regime characteristics have been extensively explored, although fire severity has not been studied as much. To build a statistical model of fire severity as a function of climate, the researchers utilised observed data for the western United States from 1984 to 2012 to create a model. This model was then used to generate twenty distinct climate change estimates for mid-century conditions (2040-2069). The model suggests that, for a significant area of the western US, fire intensity has generally decreased. However, the model takes into account variations in fuel load, fire frequency, and plant type that are influenced by the climate. Due to the disequilibrium between plant communities and climate that has been produced by humans, the prospect of a decrease in fire intensity indicated by the model may not materialise. To achieve the anticipated reduction in fire intensity, land managers in the western United States could assist in transitioning plant populations to a state of balance with the changing environment by employing active and passive restoration approaches. However, with warming temperatures and increased fire danger, fuel loads are expected to increase, making it difficult to resist changes in plant composition and fuel load through fire suppression, resulting in more severe fires in the future. In the context of a changing climate, the study highlights the advantages and disadvantages of resisting or encouraging changes in vegetation composition and fuel load.

According to Young et al. Young, Higuera, Duffy and Hu (2017), the boreal forests and arctic tundra, which cover one-third of the earth's surface, are believed to contain fifty percent of the world's soil carbon. Wildfires play a vital part in the terrestrial carbon cycle, and an increase in fire activity in these places would have global repercussions. To predict how the fire regime may evolve through time and space, the researchers examined climatic and terrain variables to estimate the 30-year chance of fire occurrence in Alaska using a spatially explicit methodology. BRT models were used to collect information on the distribution of fire in the boreal forest and tundra ecoregions. The most significant factors influencing historical fire regimes were found to be summer temperature and yearly moisture availability. Fire likelihood was found to increase nonlinearly beyond an average July temperature of 13.4°C and below a yearly moisture availability of approximately 150 mm. The BRTs were modified using climate estimates from Phase 5 of the Coupled Model Intercomparison Project under the RCP 6.0 scenario to predict fire regime responses to climate change in the 21st century. The findings indicate an increased likelihood of wildfires in Alaska's boreal forest and tundra ecosystems throughout the 21st century, with different magnitudes throughout time and space. Due to climate change, there is a possibility of up to a fourfold increase in the risk of fire in the next 30 years, which could particularly affect regions like the tundra and the forest-tundra interface, which have had low flammability in the past. The study suggests that changes in fire activity due to climate change may result in the emergence of unique fire regimes in these ecosystems, which is different from what has been observed in the past 6000-35,000 years.

Future disturbances to fire activity could endanger ecosystems and human health. However, there are few worldwide fire projections and even fewer from a variety of global climate models (GCMs). In their study, Moritz et al. Moritz, Parisien, Batllori, Krawchuk, Van Dorn, Ganz and Hayhoe (2012) employed environmental variables and global fire information to develop spatial statistical models of fire likelihood at a resolution of 0.5°, investigating the environmental factors that influence fire activity. To assess the scale and direction of change between 2010-2039 and 2070-2099, the researchers used climate norms from 16 GCMs (A2 emissions scenario) to drive fire models. The study identifies regions where the ensemble data from multiple GCMs agree on increased or decreased fire activity and regions where the models differ. Despite variations in sensitivity to biomass productivity limitations and meteorological conditions that promote burning, significant and rapid changes in future fire activity are expected in a large portion of the world's biomes. Biomes with already warm temperatures experience the most consistent increases in fire activity over the short term, while a few tropical and subtropical biomes experience more moderate declines. In more than fifty percent of terrestrial regions, model estimates regarding the near-term direction of change are contradictory, indicating that the next few decades are fraught with great uncertainty. By the end of the century, the extent and consistency of change in fire activity are anticipated to grow significantly. The majority of long-term model agreement on decreasing probabilities (20%) is observed in the tropics, while the majority of long-term model agreement on increasing fire probabilities (62%) is observed in the mid-to-high latitudes. Although long-term environmental norms captured chronic fire probability patterns very well in the global models, more research is needed to understand the additional explanatory power provided by interannual fluctuations in climatic variables. This study is the first to analyse global fire activity disturbances using an empirically grounded statistical methodology and a multi-model ensemble of GCM forecasts Ahmed, Sachindra, Shahid, Demirel and Chung (2019), which is an essential step in determining the vulnerability of people and the ecosystems they depend on to fires.

7.2. Soil erosion and deposits

Wildfires can have devastating impacts on the soil, leading to severe erosion, landslides, and other forms of soil degradation. These impacts can result in a cascade of consequences for ecosystems, water resources, and human communities. Understanding and managing the impacts of wildfires on soil is crucial for protecting the environment and preserving the sustainability of affected regions Foster (2001). Models for soil erosion and deposit have been developed to predict and comprehend the impact of wildfires on the soil. These models simulate the erosion and deposit processes that occur after a wildfire event by considering factors such as slope, soil type, vegetation cover, and rainfall intensity. The outcomes of these models provide important insights into the degree and intensity of soil degradation and can help identify areas that are most susceptible to these effects. This information can be utilised to make informed decisions on post-fire restoration, land management, and rehabilitation efforts as well as related policies Lal (2002). One such example is the Revised Universal Soil Loss Equation (RUSLE), a commonly utilised model for soil erosion that can also be applied to areas affected by wildfires. This model considers factors such as rainfall erosivity, slope gradient, soil erodibility, and vegetative cover, providing estimations of soil erosion and sediment yield. Another relevant model is the Soil Water Assessment Tool, a hydrologic and water quality model based on physical principles, that can predict soil erosion and sedimentation following wildfire events Rosero and Rastogi (2010). Soil erosion and deposit models play a crucial role in understanding the impacts of wildfires on soil and the environment and are essential for informing effective management and policy decisions related to wildfire response, recovery, and rehabilitation efforts.

Mallinis et al. Mallinis, Maris, Kalinderis and Koutsias (2009) recognise that the natural ecosystem and artificial environment are seriously threatened by forest fires in the Mediterranean area. Land degradation and desertification are effects of post-fire soil loss in the impacted regions. Furthermore, the WUI's observed expansion will probably have more severe effects on infrastructure and human resources. Soil loss-related dangers must be predicted using reliable, quick-to-implement processes in order to help prioritise mitigation efforts and substitute labour-intensive, time-consuming ones. The authors employed an analytical technique for risk assessment to evaluate the need for immediate local and regional mitigation measures following significant fire events. They utilised medium-resolution satellite images to assess the severity of post-fire damage and to determine pre-fire land cover. A geographical information system (GIS) framework was utilised to develop a model for predicting the risk of soil erosion over time. Additionally, a semi-quantitative model called the EPM was used to estimate the severity of erosion and to predict annual sediment output at the watershed level by integrating spatial data on geology, soil, and land use/cover in a GIS environment. Additionally, a parameter not currently taken into account in estimates of the danger of post-fire soil erosion was estimated using a variety of landscape measures. The suggested methodology is easily adaptable to other scales and spatial configurations, however, the approach presents a challenge because visual evaluation is used instead of lengthy field measurements to verify the conclusions.

Buckland et al. Buckland, Bailey and Thomas (2019) recognise that in dryland areas, global environmental problems can arise from land degradation and silt remobilisation. Understanding how external disturbances influence the behaviour of landforms is crucial because previously stabilised dune systems may reawaken due to climate change and human activity. Using artificial neural networks (ANNs), the authors devised a novel method for analysing past reactivation-deposition occurrences in the Nebraska Sandhills. Their goal was to determine the association between previous sand deposition in semi-arid grasslands and numerous environmental parameters, such as land use pressure, wildfire occurrences, and meteorological conditions outside the region. It was shown that both periods of plant development and sediment re-deposition may be measured. Sensitivity analysis of each individual element shows that, when the climate is kept at its current circumstances, localised forcings have a statistically significant effect. The drought brought on by the climate is, however, the main influence. The suggested method has enormous promise for assessing the sensitivity of the landscape to anticipated changes in land use and climate in a variety of potentially sensitive locations.

7.3. Smoke and particulate levels

Smoke and particulate levels resulting from wildfires have significant impacts on both human health and ecosystems. These pollutants can lead to respiratory issues, reduced visibility, and disruption of daily life. Thus, it is vital to comprehend and manage smoke and particulate levels for the purpose of wildfire adaptation and restoration. Accurate prediction and measurement of smoke and particulate levels can be achieved through the use of smoke and particulate level models. These models can aid in identifying areas at higher risk for smoke and particulate pollution, providing valuable information for wildfire response and recovery efforts. As such, the utilisation of smoke and particulate level models has become an important aspect of wildfire management and policy. The use of smoke and particulate level models have been widely researched and documented in the literature. In their study, Lee et al. Lee, Park and Kim (2018) used a numerical atmospheric model to simulate smoke dispersion and evaluate the impacts of wildfires on air quality. Clements et al. Clements, Hptom, Strand, De Groot and Klaassen (2019) employed a fire-atmosphere model to simulate the emission of smoke and particulates from wildfires and evaluate their effects on air quality in the surrounding region. Such research emphasises the significance of models that assess smoke and particulate levels in comprehending the impact of wildfires on human health and air quality. Smoke and particulate levels produced by wildfires pose a considerable risk to ecosystems and human health. Models for smoke and particulate levels provide a valuable means of predicting and measuring such levels, and of guiding wildfire response and recovery management and policy decisions. There is a need for additional research to enhance the precision and dependability of these models and to ensure their effective application in the context of wildfire adaptation and restoration.

Yao et al. Yao, Brauer, Raffuse and Henderson (2018a) acknowledge that a large number of acute cardiopulmonary events have been linked to exposure to wildfire smoke for periods longer than 24 hours. The health effects of sub-daily smoke exposure remain poorly understood due to the absence of geographically and temporally defined estimates of smoke exposure. Low-cost and universally applicable technologies are required for accurate quantification of exposure. In this study, the authors calculated the 1-hour exposure of the general population to fine particulate matter during the wildfire season in British Columbia, Canada, from 2010 to 2015 using a 5 km by 5 km resolution and an RF ML approach. Multiple sources of spatial information, remote sensing of fire activity, and meteorological data are incorporated into the suggested technique. The predictions of the model were correlated with the data at a rate of 0.93, with a root mean square error of 3.2 g/m3, a mean fractional bias of 15.1%, and a mean fractional error of 44.7%. The spatial cross-validation found an overall correlation of 0.60, ranging between 0.48 and 0.70 across monitors. If applied, this method could improve epidemiological studies on sub-daily exposure to wildfire smoke and inform real-time public health measures. The method is applicable worldwide, including in areas without air quality monitoring Holm, Miller and Balmes (2021).

Yao et al. Yao, Raffuse, Brauer, Williamson, Bowman, Johnston and Henderson (2018b) recognise that as a result of climate change, there will be more severe and frequent fires, which is a serious public health risk. Most products have limitations in measuring contaminants in the complete column of the atmosphere rather than the surface concentrations that are most relevant to population health. Although remote sensing can aid in the evaluation of exposure, its use in health studies is limited, and an understanding of the vertical distribution of smoke is needed to overcome this limitation. Due to its limited ground coverage, the CALIPSO satellite cannot collect all smoke events despite its ability to produce such data. The scientists constructed an RF model to predict the minimum height of the smoke layer that CALIPSO can detect with its great temporal and spatial resolution. The researchers utilised data on fire activity and weather conditions to inform their model, which can be easily updated in almost real-time. According to the authors, between 2006 and 2015 in British Columbia, Canada, smoke affected 15,617 CALIPSO data blocks, with 52.1% of them being in close proximity to populated regions Nazaryan, McCormick and Menzel (2008). The final model had a root mean squared error of 560 m and accounted for 82.1% of the observed variations. The model parameters that held the most significance were wind patterns, the month of smoke observation, and fire intensity within a 500-kilometer radius. The outcomes from the model can be applied to identify smoke in current remote sensing products, calculate vertical dispersion in deterministic smoke models, or incorporate remote sensing data into statistical smoke models. These potential uses could enhance assessments of the population's exposure to ground-level forest fire smoke.

Zou et al. Zou, O'Neill, Larkin, Alvarado, Solomon, Mass, Liu, Odman and Shen (2019) recognise that the western U.S. is seriously threatened by large wildfires. The Pacific Northwest had a large number of wildfires during the 2017 fire season. In order to examine the effects of wildfire smoke on public health, numerical models and measurements were combined for local fire occurrences in August and September 2017 in order to evaluate the consequences of wildfire smoke. To mimic the transport and dispersion of fire smoke, the researchers developed a one-way linked system comprising weather research and forecasting and community multiscale air quality models. In order to minimise modelling bias in fine particulate matter (PM2.5) and improve smoke exposure estimates, they integrated the high-resolution Multi-Angle Implementation of Atmospheric Correction satellite aerosol optical depth She, Zhang, Wang, Wang and Shi (2019) with the U.S. EPA AirNow ground-level monitoring PM2.5 concentrations Al-Saadi, Szykman, Pierce, Kittaka, Neil, Chu, Remer, Gumley, Prins, Weinstock, MacDonald, Wayland, Dimmick and Fishman (2005) into the modelling results. The study included three ML data fusion techniques: generalised boosting, the RF approach, and the conventional multi-linear regression technique. Particularly, the RF technique demonstrated an increase in surface PM2.5 estimates following data integration and bias reduction using 10-fold cross-validation. The optimised high-resolution PM2.5 exposure was then used to forecast a short-term exposure-response function in order to assess the acute health impacts of fire smoke. The study estimated that the overall regional mortality due to PM2.5 exposure during the smoke event was 183 (95% confidence interval: 0, 432). The fire emissions were responsible for 85% of the PM2.5 pollution and 95% of the resulting multiple-cause deaths. These findings highlight the negative health effects of fire smoke in the Pacific Northwest and underline the necessity for an effective fire smoke forecasting and reanalysis system to decrease the public health concerns associated with smoke hazards in fire-prone areas D'Evelyn, Jung, Alvarado, Baumgartner, Caligiuri, Hagmann, Henderson, Hessburg, Hopkins, Kasner, Krawchuk, Krenz, Lydersen, Marlier, Masuda, Metlen, Mittelstaedt, Prichard, Schollaert, Smith, Stevens, Tessum, Reeb-Whitaker, Wilkins, Wolff, Wood, Haugo and Spector (2022).

Reid et al. Reid, Jerrett, Petersen, Pfister, Morefield, Tager, Raffuse and Balmes (2015) highlight that it is difficult to estimate population exposure to particulate matter during wildfires due to a lack of monitoring data that adequately represents the spatiotemporal variability of smoke plumes. To solve this issue, spatial-temporal data generated by chemical transport models (CTMs) and satellite retrievals can be utilised to estimate PM2.5 concentrations during wildfires. Using a pool of 11 statistical algorithms and 29 predictor variables, 10-fold cross-validation (CV) was used to quantify PM2.5 concentrations during the 2008 Northern California wildfires in order to select the best prediction model. Several criteria, including CTM output, satellite aerosol optical depth measurements, distance to the nearest fires, meteorological data, land use, traffic, spatial position, and temporal characteristics, were utilised in this investigation. With 29 predictor variables and a CV-R2 of 0.803, the generalised boosting model (GBM) had the lowest CV root mean squared error. The distance to the nearest fire cluster, CTM output Shi, Zhang, Wang, Zhao, Chai and Zhao (2021), and GOES Aerosol/Smoke Product (GASP) Prados, Kondragunta, Ciren and Knapp (2007) Aerosol Optical Depth (AOD) Li, Ge, He and Abbas (2021) were identified as the three most crucial factors. As revealed by Cukjati et al. Cukjati, Mongus, Žalik and Žalik (2022), ML algorithms were applied to combine spatiotemporal data from satellites and CTMs in order to successfully estimate PM2.5 concentrations during severe wildfire occurrences. PM2.5 could also be accurately predicted by sparse models employing various combinations of fewer variables.

The authors assessed the dispersion of carbon monoxide (CO) emissions from a peat fire next to a roadway using a novel differential neural network model. Lozhkin et al. Lozhkin, Tarkhov, Timofeev, Lozhkina and Vasilyev (2016) created techniques for model optimisation based on simulated and actual measurements of CO concentrations in the region of smoke cloud dispersion. Numerical solutions to the problem were presented as Gaussian model approximations of neural networks and as neural network approximations of solutions to partial differential equations. When wind speed, direction, and other fire parameters change, the trained neural network model can be utilised to foresee an emergency. The study's findings show that the developed approaches are effective for managing and predicting air quality, as well as anticipating and averting such catastrophes.

The authors of the study, as noted by Watson et al. Watson, Telesca, Reid, Pfister and Jerrett (2019), acknowledge that prediction models are employed by epidemiologists to estimate (i.e., scale down) air pollution exposure when monitoring data is limited. Using ML prediction models, the study tested the accuracy of ten algorithms for predicting ground-level ozone during a 2008 wildfire occurrence in northern California Hayasaka and Skinner (2008). In order to reduce the optimistic bias of k-fold cross-validation and the conservative bias of leave-k-locations-out cross-validation, the study used leave-one-location-out cross-validation (LOLO CV) to test models and create more accurate prediction error estimates. The gradient boosting algorithm yielded the best accuracy (0.677) and lowest estimated root mean square error (0.228) among the 10 ML techniques tested, possibly due to accounting for geographical and temporal dependencies in the data. The LOLO CV was used to evaluate the models, and the RF algorithm was the second-best performance with a LOLO CV of 0.661. The LOLO CV estimates of prediction accuracy were less pessimistic than the 10-fold CV estimates for each of the ten models. There was a substantial difference in projected accuracy between 10-fold CV and LOLO CV for gradient boosting and RF models with better modelling flexibility. The selection of optimal models or covariate sets may differ between 10-fold CV and LOLO CV, calling into doubt the usefulness of 10-fold CV as a tool for model selection. The evaluation measure used affected the projected model accuracy ranking. The models used for predicting ozone exposure were designed for interpolation, not extrapolation to other geographical or spatiotemporal areas, nor for predicting the impact of wildfires on ozone. This statement is supported by the fact that models failed to appropriately estimate ozone levels during the 2007 southern California wildfires Keeley, Safford, Fotheringham, Franklin and Moritz (2009).

The authors of the study, Fuentes et al. Fuentes, Tongson, De Bei, Gonzalez Viejo, Ristic, Tyerman and Wilkinson (2019), recognise that due to the increase in frequency and intensity of bushfires as a result of climate change, smoke contamination of grapevines and grapes is becoming more common. When this occurs near vineyards, it can impact wines and cause smoke taint. However, there are currently no effective field methods to identify smoke pollution or taint in berries. The authors propose a non-invasive method for detecting smoke contamination in grapevine canopies that can be done in the field. The method is based on analysing expected changes in stomatal conductance patterns using infrared thermal images and modelling through pattern recognition. In addition, they built a second model that uses near-infrared spectroscopy data as inputs for ML fitting modelling in order to estimate the amounts of smoke-taint-related compounds in berries and wines Samadi, Wajizah and Munawar (2020). The scientists discovered that the pattern recognition algorithm accurately detected smoke pollution from canopies 96 percent of the time. The second model, which used NIR data to predict smoke taint components in berries and wine, had a correlation coefficient of 0.97 and no signs of overfitting. These technologies provide grape growers with a non-destructive, cost-effective, and precise in-field screening tool to support vineyard management measures designed to reduce smoke taint in wines. Additionally, mobile devices and unmanned aerial systems (UAS) can be used in conjunction with these techniques Mirabelli-Montan, Marangon, Graça, Marangon and Wilkinson (2021).

The following table presents an overview of various Wildfire Restoration and Adaptation Models, with a specific focus on the impact of climate change, soil erosion and deposits, and smoke and particulate levels. This table characterises these models based on several critical categories, including weather observations, historical data, environmental factors, fire data, socio-economic factors, and the methods used to predict and respond to the impacts of wildfires. By analysing these factors, this table provides a comprehensive understanding of the various approaches used to restore and adapt ecosystems and communities after a wildfire. This resource is invaluable for individuals and organisations working in the field of wildfire management and restoration, as it offers a clear understanding of the factors that influence the success of restoration and adaptation efforts and the methods used to address them.

Table 3: Summary of Restoration and Adaptation Models

Reference	Weather Observations	Historical Data	Environmental Factors	Fire Data	Socio-Economic Factors	Method
Amatulli et al. Amatulli et al. (2013)	The European Centre for Medium-Range Weather Forecast's 40-Year Re-analysis (ERA-40) Data Archive was mined for meteorological information (ECMWF)	Meteorological data were collected from the 40-Year Re-analysis (ERA-40). The historical records in the database used for this study span the years 1985 to 2004 (20 years), plus two additional years (2005–2006) used for validation purposes.	The Regional Climate Model (RCM) HIRHAM,	The European Fire Database of EFFIS has been mined for fire data.	NUTS3 level in Portugal	MLR, RF, MARS
Parks et al. Parks et al. (2018)	Not applicable	Observed data for the western United States from 1984 to 2012	Not applicable	Fire frequency and area burned	Not applicable	A statistical model of fire severity as a function of climate, BRT
Yao et al. Yao et al. (2018a)	NASA's Modern Era Retrospective-analysis for Research and Applications (MERRA) programme was used to retrieve hourly meteorological information. Geller and Stoner (2017)	The severe fire seasons in 2010, 2014, and 2015	British Columbia's Ministry of Environment and Climate Change Strategy's Provincial Air Data Archive website provides hourly average PM2.5 measurements from 72 air quality monitoring stations.	Data from the MODIS instruments onboard the Aqua and Terra satellites in polar orbit 155s	Human populations smoke exposal.	An RF model to estimate 1-hour average population exposure to fine particulate matter
Yao et al. Yao et al. (2018b)	Not applicable	Forest fire seasons 2006-2015	The GTOPO30 product created by the US Geological Survey EROS Center	The Fire Information for Resource Management System by NASA	Human populations smoke exposal.	An RF model that predicts the minimal height of the smoke layer observed by CALIPSO with high temporal and spatial resolution.
Zou et al. Zou et al. (2019)	3.7 version of the Weather Research and Forecasting (WRF) model and 5.2 version of the Community Multiscale Air Quality (CMAQ) model.	Not applicable	U.S. EPA AirNow monitors PM2.5 concentrations at ground level.	The CMAQ system's Sparse Matrix Operator Kernel Emissions model.	The 2010 US Census Grids provided by NASA's Socioeconomic Data and Applications Center and the Centers for Disease Control and Prevention's Wide-ranging ONline Data for Epidemiologic Research (WONDER) were mined for demographic data.	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. Reid et al. (2015)	The National Center for Atmospheric Research (NCAR) provided PM2.5 concentration estimates derived from the Weather Research and Forecasting with Chemistry zWRF-Chem 3.2 model.	Not applicable	The California Air Resources Board (CARB), and the AirNow and AirFire databases	2008 wildfires in northern California as depicted by the US Forest Service's Remote Sensing Applications Center using MODIS Fire Detection points.	During wildfires, estimating human exposures that may differ on small spatial scales.	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. Lozhkin et al. (2016)	Not applicable	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. Watson et al. (2019)	Weather Research and Forecasting with Chemistry (WRF-Chem)	Not applicable	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. Fuentes et al. (2019)	Micrometeorological weather data such as temperature, relative humidity, and solar radiation	Not applicable	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. Young et al. (2017)	Monthly mean temperature and total precipitation data from the climate research unit	The historical period from 1950–2009	Alaska, the boreal forest, and the tundra	30 (non-continuous) years of paired fire data	Not applicable	BRT
Moritz et al. Moritz et al. (2012)	Global climate model output from the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 multi-model dataset	The historical period from 1971–2000	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
Mallinis et al. Mallinis et al. (2009)	GIS weather data	Not applicable	GIS environmental data	GIS fire data	Not applicable	CART and KM

Buckland et al. Buckland et al. (2019)	The Niobrara Valley Preserve provided an integrated record of precipitation and temperature change over the past 400 years	The Niobrara Valley Preserve provided an integrated record of over the past 400 years	Not applicable	Wildfire occurrence data	ANN defines the relationship between climatic and human disturbance forces	ANNs

8. Discussion and Lessons Learned

In recent years, the study of prevention and preparedness models for wildfires has become a major area of research, taking into account a multitude of factors such as fire weather forecasts, fire occurrence forecasts, fire management and planning, and various social factors. A comprehensive survey was conducted that utilised a wide range of research sources that focused on the impact of weather information, environmental and socioeconomic factors, and historical data on landscape management and its contribution to fire occurrences. The results of this study showed that most existing wildfire prevention and mitigation strategies are focused on mitigating the negative effects of wildfires rather than addressing the root cause of the problem. Given the significant role that human behaviour plays in wildfires, which is often the most unpredictable factor, it is crucial to tackle the root cause of the problem when dealing with man-made disasters. To achieve this, models that take into consideration a wide range of factors are more likely to be effective in both prevention and preparedness efforts. Advancements in remote sensing technology, such as the Advanced Very High-Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and VIIRS, have played a critical role in improving the monitoring and observation of wildfires. These sensors, which are onboard satellites such as NASA, TERRA and AQUA, and NOAA GOES, regularly track changes in vegetation and its distribution. Advances in NWP and climate models have also enabled higher resolution forecasting and longer lead time predictions, which may improve the predictability of extreme fire weather events. With sufficient data, these developments have allowed for a data-centric approach to modelling wildfires, making them a natural evolution for many research challenges. Studies of these models have shown great potential for accurately and quickly identifying future wildfire outbreaks and making response activities more efficient, safe, and quick. This research also aims to address the problems related to restoring biospheres and ecosystems after wildfires, as well as adapting to the new conditions brought on by climate change. The relationship between post-fire characteristics of a landscape and local fuel typology, plant health, and overall burn intensity has been examined. The results show that the intensity of the impacts of wildfires on soil and its capacity to absorb and process water is directly related to the density of pre-fire vegetation and the length of the fire burn.

A comprehensive review of techniques for forest fire prediction and detection was conducted as part of this study. The analysis of existing literature revealed that algorithms, particularly neural networks and LR, are widely used in this domain, with an increasing focus on incorporating AI in forest fire modelling. The use of multi-sensor data in a neural network-based forest fire detection model has been found to have several benefits, such as reducing false alarms and communication costs and improving energy efficiency. Deep ANNs, specifically CNNs, have been found to be promising for fire modelling. Other algorithms, such as SVMs, Bayesian models, and FL, are used less frequently but have their own strengths and limitations that may make them more suitable for certain applications. For example, SVMs are known for their ability to handle complex non-linear relationships, while Bayesian models are well-suited for probabilistic prediction and uncertainty analysis.

The use of various technologies and techniques has greatly improved wildfire prediction and management. Electronic lightning detection systems, NWP, and satellite data have been combined to provide early warning of fire danger conditions. These technologies can also help build regression associations to anticipate NWP using lightning prediction models, improving the accuracy of predicting wildfires. FOP models using ML techniques have also been used to improve predictions of fire occurrence by incorporating more sophisticated algorithms and data sources, such as remote sensing data and weather forecasts. Planning and policy models have also been used to assess the effectiveness of existing policies and management strategies, identify areas for improvement, and allocate resources more efficiently. However, the use of ML in fire control issues has been relatively scarce, providing significant potential for innovative solutions. In conclusion, a combination of these technologies and techniques can help to minimise the damages caused by wildfires and ensure the safety of people, wildlife, and the environment, making wildfire prediction and management more effective.

Accurate prediction of fire spread behaviour is critical for effective wildfire management. Remote sensing data, including Landsat land cover data, NOAA weather measurements, and archived MODIS sensor data, has proven beneficial in understanding wildfire dynamics. Fuel properties play a vital role in determining fire behaviour, and the accurate prediction of fuel properties is essential for effective fire management. ML algorithms, such as RF and CNNs, which have the potential to significantly advance our understanding and ability to predict and manage wildfires. Fire susceptibility mapping using algorithms such as MaxEnt, BRT, or RF can help identify areas at higher risk of wildfires and prioritise resources for fire prevention and suppression efforts. Remote sensing methods, such as satellite and aerial imagery, thermal infrared, and lidar sensors, can provide detailed and precise information on active fires and burn severity, which is valuable for measuring the fire's economic and ecological impacts and for recovery planning. The integration of remote sensing ML algorithms has the potential to significantly enhance our ability to predict and manage wildfires in the future.

Climate change is a global challenge that affects ecosystems, biodiversity, and human communities. Transfer modelling, a popular approach in climate change science, is used to apply models developed for one study region to other locations. ML techniques have demonstrated their potential in species distribution modelling and simulating the effects of climate change on forest fires, outperforming traditional statistical models. However, it is crucial to thoroughly assess and validate these models before implementing them in new contexts to ensure their reliability and accuracy. Models for soil erosion and deposit and smoke and particulate levels resulting from wildfires are crucial in understanding the impacts of wildfires on soil, ecosystems, human health, and air quality. These models provide valuable insights into the degree and intensity of soil degradation and can aid in identifying areas that are most susceptible to these effects. They also provide a means of predicting and measuring smoke and particulate levels and guiding wildfire response and recovery management and policy decisions. Further research is needed to enhance the precision and reliability of these models and ensure their effective application in the context of wildfire adaptation and restoration. Lessons learned include the importance of ML techniques and models for effective wildfire management and policy decisions, the need for thorough assessment and validation of these models, and the significance of continued research to enhance their precision and reliability.

Despite the valuable solutions mentioned before, there is still room for optimising the wildfire management systems, taking full advantage of novel technologies. First, the implementation of beyond 5G networks can bring about a new era in wildfire management. The high-speed, low latency, and high-capacity nature of beyond 5G networks can allow for real-time monitoring, detection, predictive maintenance Giannakidou, Radoglou-Grammatikis, Koussouris, Pertselakis, Kanakaris, Lekidis, Kaltakis, Koidou, Metallidou, Psannis et al. (2022) and communication of wildfires. The high-speed nature of beyond 5G networks can significantly reduce the time required to process the vast amounts of data generated by remote sensing technologies and NWP models, allowing for the prediction of wildfires with greater accuracy. In addition, beyond 5G networks can be used to improve the coordination of firefighting efforts. The ability of beyond 5G networks to provide reliable, high-speed communication can help emergency responders and firefighting teams to quickly exchange information, share updates on fire locations and firefighting strategies, and coordinate their actions. Furthermore, the use of beyond 5G networks can help ensure that critical information is transmitted in real-time to all relevant parties, allowing for a more effective and efficient response. Another potential benefit of beyond 5G networks in the context of wildfire management is the ability to support drones. The use of drones can provide valuable aerial reconnaissance and fire mapping data, as well as real-time video feeds from the fire front. The high-speed, low latency and high-capacity nature of beyond 5G networks can ensure that the data collected by UAVs can be transmitted in real-time to emergency responders and firefighting teams, allowing for a more effective response.

The management of wildfires is another area where SDN can play a crucial role. Specifically, SDN facilitates the development of adaptable and programmable networks, which can lead to preventative measures against wildfires. Network resource optimisation and fire prevention can be achieved by SDN's centralised management by enforcing policies and traffic engineering rules. For instance, SDN can reroute traffic around potentially dangerous nodes, restrict access to certain portions of the network, and adapt network settings in real-time. By facilitating better communication and coordination between emergency personnel, SDN can aid in firefighting efforts. The programmability of SDN allows first responders to prioritise life-saving communications, dynamically assign bandwidth, and set up secure lines of contact in disaster zones. Mobile communication networks, drone networks, and sensor networks can all be deployed with the use of SDN to improve situational awareness and aid in firefighting efforts. Finally, after a wildfire, SDN can help with cleanup and repair efforts. SDN's network programmability allows for a more effective distribution of resources for things like rebuilding after a fire, getting people back online, and repairing damaged infrastructure. Because of SDN's centralised management, restoration efforts can be better coordinated, and resources may be used more effectively. Finally, SDN's capacity to be programmed, managed centrally, and controlled dynamically makes it a potent tool for bettering the control of wildfires. To lessen the effects of wildfires, businesses can use SDN technology to get a jump on warnings, take preventative steps, speed up firefighting and cleanup, and analyse the resulting data more efficiently.

The digital twins are another cutting-edge technology that can make a significant contribution to wildfire management. However, there are no holistic digital twins that can efficiently emulate wildfire cases. A virtual replica or representation of a real-world process, system, or object is referred to as a `Digital Twin`. Digital twins can be developed in the context of wildfire management to simulate and model different aspects of wildfires, facilitating better comprehension and decision-making. In order to create a real-time representation of the wildfire situation, digital twins can first combine different data sources, such as satellite imagery, weather data, sensor networks, and historical fire data. Potential wildfire outbreaks can be identified early through analysis and correlation of this data within the digital twin, enabling prompt response and intervention. Second, using data from environmental conditions, topography, vegetation, and other relevant variables, digital twins can simulate and model how wildfires spread. Land managers, firefighters, and policymakers can evaluate the efficacy of various prevention strategies by running predictive scenarios within the digital twin. This covers resource allocation, fuel management, planning for defendable space, and strategic planning for controlled burns. Advanced fire behaviour models can be incorporated into digital twins to simulate the spread of fire under various conditions. Digital twins can help with evacuation planning, resource allocation, and assessing the potential impact on vital infrastructure and communities by taking factors like wind speed, fuel moisture, and topography into account. Digital twins can also help with damage assessment, ecosystem impact modelling, and restoration activity planning following a wildfire event. Digital twins can help with the design of efficient restoration strategies, monitoring of progress, and evaluation of the long-term recovery of the affected areas by incorporating data on vegetation recovery, soil erosion, hydrological impacts, and ecosystem dynamics. Finally, by intuitively visualising complex data and simulations, digital twins offer a platform for decision support. During wildfire events, they can help incident commanders, emergency management teams, and land managers make well-informed decisions regarding resource allocation, evacuation planning, and the hierarchy of response initiatives. Digital twins provide a comprehensive approach to wildfire management by fusing real-time data, sophisticated modelling, and analytics. They give stakeholders the ability to evaluate risks, investigate scenarios, and put preventative measures in place to lessen the effects of wildfires. For the detection, prevention, and restoration of wildfires, the insights offered by digital twins can improve situational awareness, response coordination, and long-term planning. Finally, the role of AI in digital twins is critical since AI generative techniques, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Autoregressive Models and Transformers can generate realistic data that can optimise the emulation services of the digital twins.

Federated learning appears to be a game-changing technology with immense potential for fire management. Federated learning eliminates the need for a centralised data repository when training ML models in a group context with data from multiple sources. Federated learning can incorporate data from a variety of locally-based sensors, cameras, and distributed sources for the detection of wildfires without compromising individual privacy. This collaborative strategy facilitates the development of a robust and dependable system for detecting wildfires by combining information and models from multiple locations. In addition to assisting in the development of prediction models for assessing the risk of wildfires, federated learning is also useful for risk assessment. Using data gathered from a variety of local environmental and meteorological conditions, ML algorithms can predict areas prone to fire and identify contributing factors. This data is useful for regional-scale fire management, including the implementation of controlled burning, the optimisation of resource allocation, and the development of effective management strategies. Moreover, federated learning streamlines the interpretation of post-fire data collected from a variety of sources, such as satellite imagery, environmental sensors, and ground surveys. Using models trained on distributed datasets, it is possible to perform damage assessments, monitor recovery progress, and forecast long-term ecological consequences of wildfires. This invaluable information is used to direct restoration efforts, establish resource priorities, and inspire the development of effective ecosystem recovery techniques.

Next, wildfire detection, prevention, and restoration activities may benefit from the use of blockchain technology because of its potential to improve data integrity, traceability, and decentralised collaboration. Blockchain technology allows for the immutable and transparent recording of data from weather sensors, satellite photography, and ground-based observations. By safeguarding data and preventing unauthorised alterations, this facilitates trustworthy analysis and decision-making for detecting wildfires. Smart contracts and DApps, made possible by blockchain's decentralised nature, automate stakeholder agreements and procedures to make preventative measures easier to adopt. Smart contracts, for instance, can ensure that fire safety regulations are followed, oversee controlled burns, and encourage sustainable land use. Blockchain-based DApps can facilitate wildfire prevention collaboration by offering a trusted environment for the exchange of data and the coordination of efforts among many parties. By allowing firefighters, emergency services, and authorities to share information in real time, blockchain technology enhances communication, coordination, and resource allocation during firefighting operations. It makes it easier to make decisions under pressure and guarantees openness. In addition, the validity and integrity of command chain communications can be verified via blockchain. In terms of restoration, blockchain can record operations, resource allocation, and progress on a transparent ledger, allowing for tracking and verification of restoration efforts. This facilitates responsibility, efficient use of resources, and accurate tracking of money set aside for restoration efforts. Furthermore, blockchain can facilitate the development of decentralised marketplaces, linking together post-fire rehabilitation organisations, funders, and volunteers. Last but not least, blockchain technology allows for private and decentralised data sharing between parties involved in wildfire management, protecting personal information while also boosting teamwork. Incentives for data sharing and collaboration through blockchain-based data marketplaces and provenance procedures can propel wildfire management research and development.

Severe wildfires can have long-term impacts, such as making the soil nearly hydrophobic due to the deposit of a new layer of burned debris, which dramatically increases the rate of runoff and makes the land more vulnerable to soil erosion during storms and heavy rains. These issues pose a significant threat to impacted communities and the availability of natural resources. In conclusion, this study focuses on documenting these problems and highlights the potential of advanced technologies and data-driven models in mitigating the impact of wildfires. The use of remote sensing, NWP, and algorithms have the potential to greatly improve the monitoring and prediction of wildfires, which can result in more effective and efficient fire response activities. This research is also critical in addressing the long-term impacts of wildfires on ecosystems and communities, as well as adapting to new conditions brought on by climate change. The results of this study demonstrate the importance of a multi-disciplinary approach to tackling the root cause of wildfires and ensuring a more sustainable future.

9. Conclusions

Forest fires pose a major threat to the planet's ecological balance and human communities. To minimise the damage caused by forest fires and reduce the need for firefighting efforts, it is crucial to predict forest fires by modelling the relationship between fire risk and factors such as weather or fuel availability, as well as detecting them through various monitoring techniques. In response to this growing threat, the field of forest fire prediction and detection has become a topic of ongoing research and development, with the goal of supporting public policies for controlling forest fires and reducing the threat posed by these fires.

In conclusion, the use of advanced systems incorporating AI is a promising approach to reducing the threat posed by forest fires. The role of algorithms in forest fire prediction and detection systems is highlighted in this study, which offers a comprehensive overview of the current state-of-the-art in the field. Using these models effectively is critical in preventing and reducing the adverse effects of forest fires and wildfires, protecting human communities, and maintaining the resilience of the Earth's ecosystems.

As the threat of forest fires continues to grow, there is a growing need for more effective and efficient methods for forest fire prevention, detection, and restoration. Future plans in this field aim to integrate AI and techniques further to enhance the accuracy of forest fire prediction and detection systems. Additionally, efforts are being made to improve the speed and scalability of these systems to ensure that they can keep pace with the increasing frequency and severity of forest fires. This may involve the development of new algorithms and the integration of novel sensor technologies and remote sensing techniques. Another area of focus is to improve the integration of these systems with other existing systems and platforms to ensure that they can be effectively used in concert with other fire management strategies. Overall, the future of forest fire prevention, detection, and restoration is promising, and continued investment in this field is critical to protect human communities and the planet's ecosystems.

References

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western us forests. Proceedings of the National Academy of Sciences 113, 11770–11775. URL: https://www.pnas.org/doi/abs/10.1073/pnas.1607171113, doi:10.1073/pnas.1607171113, arXiv:https://www.pnas.org/doi/pdf/10.1073/pnas.1607171113.

Adab, H., 2017. Landfire hazard assessment in the caspian hyrcanian forest ecoregion with the long-term modis active fire data. Natural Hazards 87. doi:10.1007/s11069-017-2850-2.

Afzal, F., Yunfei, S., Nazir, M., Mahmood, S., 2019. A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. International Journal of Managing Projects in Business ahead-of-print. doi:10.1108/IJMPB-02-2019-0047.

Ager, A.A., Romans, B., 2010. Planning for wildland fire: a review of regional approaches in the western united states. Landscape and Urban Planning 94, 27–36.

Ahmed, K., Sachindra, D.A., Shahid, S., Demirel, M.C., Chung, E.S., 2019. Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum and minimum temperature based on spatial assessment metrics. Hydrology and Earth System Sciences 23, 4803–4824. URL: https://hess.copernicus.org/articles/23/4803/2019/, doi:10.5194/hess-23-4803-2019.

Al-Rawabdeh, A.S., Ahmed, T.S., 2019. Wildfire detection using machine learning techniques. Journal of Computer Science 15, 734–741.

Al-Rawi, K.R., Casanova, J.L., Romo, A., Louakfaoui, E.M., 2002. Integrated fire evolution monitoring system (ifems) for monitoring spatial-temporal behaviour of multiple fire phenomena. International Journal of Remote Sensing 23, 1967–1983. URL: https://doi.org/10.1080/01431160110069809, doi:10.1080/01431160110069809, arXiv:https://doi.org/10.1080/01431160110069809.

Al-Saadi, J., Szykman, J., Pierce, R.B., Kittaka, C., Neil, D., Chu, D.A., Remer, L., Gumley, L., Prins, E., Weinstock, L., MacDonald, C., Wayland, R., Dimmick, F., Fishman, J., 2005. Improving national air quality forecasts with satellite aerosol observations. Bulletin of the American Meteorological Society 86, 1249–1261. URL: http://www.jstor.org/stable/26221354.

Alexander, M.E., Gustafson, E.J., 2003. A framework for wildland fire management in the united states. Conservation Biology 17, 329–340.

Alexandrov, D., Pertseva, E., Berman, I., Pantiukhin, I., Kapitonov, A., 2019. Analysis of machine learning methods for wildfire security monitoring with an unmanned aerial vehicles, in: 2019 24th Conference of Open Innovations Association (FRUCT), pp. 3–9. doi:10.23919/FRUCT.2019.8711917.

Alonso-Betanzos, A., Fontenla-Romero, O., Guijarro-Berdiñas, B., Hernández-Pereira, E., Inmaculada Paz Andrade, M., Jiménez, E., Luis Legido Soto, J., Carballas, T., 2003. An intelligent system for forest fire risk prediction and fire fighting management in galicia. Expert Systems with Applications 25, 545–554. URL: https://www.sciencedirect.com/science/article/pii/S0957417403000952, doi:https://doi.org/10.1016/S0957-4174(03)00095-2.

Amatulli, G., Camia, A., 2007. Exploring the relationships of fire occurrence variables by means of cart and mars models. Researchgate .

Amatulli, G., Camia, A., San-Miguel-Ayanz, J., 2013. Estimating future burned areas under changing climate in the eu-mediterranean countries. The Science of the total environment 450-451C, 209–222. doi:10.1016/j.scitotenv.2013.02.014.

Armas, S., Baeza, M., Nava, C., Moutahir, H., 2013. Modeling the probability of wildfire occurrence in the valencian community, in: Unknown, pp. 1–2.

Arrue, B., Ollero, A., Martinez-de Dios, J.R., 2000. Arrue, b.c.: An intelligent system for false alarm reduction in infrared forest-fire detection. ieee intelligent systems and their applications 15(3), 64-73. Intelligent Systems and their Applications, IEEE 15, 64 – 73. doi:10.1109/5254.846287.

Artés, T., Cencerrado, A., Cortés, A., Margalef, T., 2016. Real-time genetic spatial optimization to improve forest fire spread forecasting in high-performance computing environments. International Journal of Geographical Information Science 30, 594–611. URL: https://doi.org/10.1080/13658816.2015.1085052, doi:10.1080/13658816.2015.1085052, arXiv:https://doi.org/10.1080/13658816.2015.1085052.

Ascoli, D., Vacchiano, G., Motta, R., Bovio, G., 2015. Building rothermel fire behaviour fuel models by genetic algorithm optimisation. International Journal of Wildland Fire doi:10.1071/WF14097.

Ba, R., Chen, C., Yuan, J., Song, W., Lo, S., 2019. Smokenet: Satellite smoke scene detection using convolutional neural network with spatial and channel-wise attention. Remote Sensing 11. URL: https://www.mdpi.com/2072-4292/11/14/1702, doi:10.3390/rs11141702.

Baker, W.L., 1991. A review of fire weather and prediction models for fire management. International Journal of Wildland Fire 1, 95–109.

Bao, S., Xiao, N., Lai, Z., Zhang, H., Kim, C., 2015. Optimizing watchtower locations for forest fire monitoring using location models. Fire Safety Journal 71, 100–109. URL: https://www.sciencedirect.com/science/article/pii/S0379711214001672, doi:https://doi.org/10.1016/j.firesaf.2014.11.016.

Barmpoutis, P., Dimitropoulos, K., Kaza, K., Grammalidis, N., 2019. Fire detection from images using faster r-cnn and multidimensional texture analysis, in: ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 8301–8305. doi:10.1109/ICASSP.2019.8682647.

Bashari, H., 2016. Risk of fire occurrence in arid and semi-arid ecosystems of iran: an investigation using bayesian belief networks. Environmental monitoring and assessment 188. doi:10.1007/s10661-016-5532-8.

Bates, B.C., Dowdy, A.J., Chandler, R.E., 2017. Classification of australian thunderstorms using multivariate analyses of large-scale atmospheric variables. Journal of Applied Meteorology and Climatology 56, 1921 – 1937. URL: https://journals.ametsoc.org/view/journals/apme/56/7/jamc-d-16-0271.1.xml, doi:10.1175/JAMC-D-16-0271.1.

Bisquert, M., Caselles, E., Sánchez-Tomás, J., Caselles, V., 2012. Application of artificial neural networks and logistic regression to the prediction of forest fire danger in galicia using modis data. International Journal of Wildland Fire 21, 1025–1029. doi:10.1071/WF11105.

Blouin, K., Flannigan, M., Wang, X., Kochtubajda, B., 2016. Ensemble lightning prediction models for the province of alberta, canada. International Journal of Wildland Fire 25. doi:10.1071/WF15111.

Bond, M.J., Bond, W.J., 2018. Community resilience and the role of social networks in the aftermath of wildfires. Natural Hazards 92, 703–722.

Bot, K., Borges, J.G., 2022. A systematic review of applications of machine learning techniques for wildfire management decision support. Inventions 7. URL: https://www.mdpi.com/2411-5134/7/1/15, doi:10.3390/inventions7010015.

Bova, S., et al., 2010. Wildfire prediction and management: A review of models and strategies. Forest Science 56, 397–407.

Bowman, D.M., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., et al., 2019. The human dimension of fire regimes on earth. International Journal of Wildland Fire 28, 634–650.

Bradley, C.M., Hanson, C.T., Dellasala, D.A., 2016. Does increased forest protection correspond to higher fire severity in frequent-fire forests of the western united states? Ecosphere 7.

Briones-Herrera, C.I., Vega-Nieva, D.J., Monjarás-Vega, N.A., Flores-Medina, F., Lopez-Serrano, P.M., Corral-Rivas, J.J., Carrillo-Parra, 2019. Modeling and mapping forest fire occurrence from aboveground carbon density in mexico. Forests 10. doi:10.3390/f10050402.

Brunet, G., 2005. The first hundred years of numerical weather prediction, in: Proceedings. 19th International Symposium on High Performance Computing Systems and Applications, IEEE Computer Society, Los Alamitos, CA, USA. pp. 276–279. URL: https://doi.ieeecomputersociety.org/10.1109/HPCS.2005.54, doi:10.1109/HPCS.2005.54.

Buckland, C., Bailey, R., Thomas, D., 2019. Using artificial neural networks to predict future dryland responses to human and climate disturbances. Scientific Reports 9. doi:10.1038/s41598-019-40429-5.

Caballero, E., Ferreira, V., Lima, R.A., Soto, J.C.H., Muchaluat-Saade, D., Albuquerque, C., 2021. Bns: A framework for wireless body area network realistic simulations. Sensors 21. URL: https://www.mdpi.com/1424-8220/21/16/5504, doi:10.3390/s21165504.

Cao, Y., Wang, M., Liu, K., 2017. Wildfire susceptibility assessment in southern china: A comparison of multiple methods. International Journal of Disaster Risk Science 8. doi:10.1007/s13753-017-0129-6.

Cao, Y., Yang, F., Tang, Q., Lu, X., 2019. An attention enhanced bidirectional lstm for early forest fire smoke recognition. IEEE Access 7, 154732–154742. doi:10.1109/ACCESS.2019.2946712.

Carvalho, Flannigan, Miranda, Borrego, 2017. Fire activity in portugal and its relationship to weather and the canadian fire weather index system. International Journal of Wildland Fire 17, 328–338. doi:10.1071/WF07014.

Center), N.N.I.F., 2020. Wildland fire management statistics.

Chang, C.C., Lee, T.Y., Wu, C.C., 2010. A review of machine learning algorithms for fire management. Expert Systems with Applications 37, 8589–8598.

Chaudhary, M.T., Piracha, A., 2021. Natural disasters—origins, impacts, management. Encyclopedia 1, 1101–1131. URL: https://www.mdpi.com/2673-8392/1/4/84, doi:10.3390/encyclopedia1040084.

Chetehouna, K., Tabach, E.E., Bouazaoui, L., Gascoin, N., 2015. Predicting the flame characteristics and rate of spread in fires propagating in a bed of pinus pinaster using artificial neural networks. Process Safety and Environmental Protection 98, 50–56. URL: https://www.sciencedirect.com/science/article/pii/S0957582015001111, doi:https://doi.org/10.1016/j.psep.2015.06.010.

Chirici, G., Scotti, R., Montaghi, A., Barbati, A., Cartisano, R., Lopez, G., Marchetti, M., McRoberts, R., Olsson, H., Corona, P., 2013. Stochastic gradient boosting classification trees for forest fuel types mapping through airborne laser scanning and irs liss-iii imagery. International Journal of Applied Earth Observation and Geoinformation 25, 87–97. URL: https://www.sciencedirect.com/science/article/pii/S0303243413000494, doi:https://doi.org/10.1016/j.jag.2013.04.006.

Chuvieco, E., 2002. Satellite remote sensing of fires and burned areas. Geology and Natural Hazards 45, 855–872.

Clements, C.B., Hptom, C.M., Strand, E.K., De Groot, W.J., Klaassen, W.G., 2019. Modeling smoke and particulate emissions from the 2015 oregon wildfires using a coupled fire-atmosphere model. Journal of Geophysical Research: Atmospheres 124, 8374–8391. doi:10.1029/2019JD030775.

Cochrane, M.K., 2011. Fire susceptibility mapping using random forest and boosted regression trees. International Journal of Wildland Fire 20, 589–600.

Costafreda-Aumedes, S., Cardil, A., Molina Terrén, D., Daniel, S., Mavsar, R., Vega-Garcia, C., 2015. Analysis of factors influencing deployment of fire suppression resources in spain using artificial neural networks. iForest - Biogeosciences and Forestry 9. doi:10.3832/ifor1329-008.

Crimmins, M.A., 2006. Synoptic climatology of extreme fire-weather conditions across the southwest united states. International Journal of Climatology 26, 1001–1016. URL: https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/joc.1300, doi:https://doi.org/10.1002/joc.1300, arXiv:https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/joc.1300.

Cukjati, J., Mongus, D., Žalik, K.R., Žalik, B., 2022. Iot and satellite sensor data integration for assessment of environmental variables: A case study on no2. Sensors 22. URL: https://www.mdpi.com/1424-8220/22/15/5660, doi:10.3390/s22155660.

Davis, R., Yang, Z., Yost, A., Belongie, C., Cohen, W., 2017. The normal fire environment—modeling environmental suitability for large forest wildfires using past, present, and future climate normals. Forest Ecology and Management 390, 173–186. URL: https://www.sciencedirect.com/science/article/pii/S0378112716309318, doi:https://doi.org/10.1016/j.foreco.2017.01.027.

De Graff, J.V., 2014. Improvement in quantifying debris flow risk for post-wildfire emergency response. Geoenvironmental Disasters 1, 5. URL: https://doi.org/10.1186/s40677-014-0005-2, doi:10.1186/s40677-014-0005-2. sN: 2197-8670.

Delgado, R., González, J.L., Sotoca, A., Tibau, X.A., 2018. Archetypes of wildfire arsonists: An approach by using bayesian networks, in: Szmyt, J. (Ed.), Forest Fire. IntechOpen, Rijeka. chapter 2, pp. 1–27. URL: https://doi.org/10.5772/intechopen.72615, doi:10.5772/intechopen.72615.

Denham, M., Laneri, K., 2018. Using efficient parallelization in graphic processing units to parameterize stochastic fire propagation models. Journal of Computational Science 25, 76–88. URL: https://www.sciencedirect.com/science/article/pii/S1877750317308773, doi:https://doi.org/10.1016/j.jocs.2018.02.007.

Dragozi, E., Gitas, I., Stavrakoudis, D.G., Theocharis, J.B., San-Miguel-Ayanz, J., 2011. A performance evaluation of support vector machines and the nearest neighbor classifier in classifying image objects for burned area mapping. Researchgate .

Duane, A., Pique, M., Castellnou, M., Brotons, L., 2015. Predictive modelling of fire occurrences from different fire spread patterns in mediterranean landscapes. International Journal of Wildland Fire 24. doi:10.1071/WF14040.

Dutta, R., Das, A., Aryal, J., 2016. Big data integration shows australian bush-fire frequency is increasing significantly. Royal Society Open Science 3, 150241. doi:10.1098/rsos.150241.

D'Evelyn, S.M., Jung, J., Alvarado, E., Baumgartner, J., Caligiuri, P., Hagmann, R.K., Henderson, S.B., Hessburg, P.F., Hopkins, S., Kasner, E.J., Krawchuk, M.A., Krenz, J.E., Lydersen, J.M., Marlier, M.E., Masuda, Y.J., Metlen, K., Mittelstaedt, G., Prichard, S.J., Schollaert, C.L., Smith, E.B., Stevens, J.T., Tessum, C.W., Reeb-Whitaker, C., Wilkins, J.L., Wolff, N.H., Wood, L.M., Haugo, R.D., Spector, J.T., 2022. Wildfire, smoke exposure, human health, and environmental justice need to be integrated into forest restoration and management. Current Environmental Health Reports 9, 366–385. URL: https://doi.org/10.1007/s40572-022-00355-7, doi:10.1007/s40572-022-00355-7. sN: 2196-5412.

El Houssami, M., Lamorlette, A., Morvan, D., Hadden, R.M., Simeoni, A., 2018. Framework for submodel improvement in wildfire modeling. Combustion and Flame 190, 12–24. URL: https://www.sciencedirect.com/science/article/pii/S0010218017303760, doi:https://doi.org/10.1016/j.combustflame.2017.09.038.

Faramarzi, H., Hosseini, S.M., Pourghasemi, H., Farnaghi, M., 2021. Forest fire spatial modelling using ordered weighted averaging multi-criteria evaluation. Journal of Forest Science 67, 87–100. doi:10.17221/50/2020-JFS.

Finney, M.A., 2005. The challenge of quantitative risk analysis for wildland fire. Forest Ecology and Management 211, 97–108. URL: https://www.sciencedirect.com/science/article/pii/S0378112705000563, doi:https://doi.org/10.1016/j.foreco.2005.02.010. relative Risk Assessments for Decision –Making Related To Uncharacteristic Wildfire.

Fischer, A., Unknown. Restoration of Natural Hydrological Systems. Unknown.

Foster, G.R., 2001. Soil erosion and conservation. John Wiley & Sons.

Fuentes, S., Tongson, E.J., De Bei, R., Gonzalez Viejo, C., Ristic, R., Tyerman, S., Wilkinson, K., 2019. Non-invasive tools to detect smoke contamination in grapevine canopies, berries and wine: A remote sensing and machine learning modeling approach. Sensors 19. URL: https://www.mdpi.com/1424-8220/19/15/3335, doi:10.3390/s19153335.

García, M., Riaño, D., Chuvieco, E., Salas, J., Danson, F.M., 2011. Multispectral and lidar data fusion for fuel type mapping using support vector machine and decision rules. Remote Sensing of Environment 115, 1369–1379. URL: https://www.sciencedirect.com/science/article/pii/S0034425711000393, doi:https://doi.org/10.1016/j.rse.2011.01.017.

Geller, M.A., Stoner, A.M., 2017. Modern era retrospective-analysis for research and applications (merra). Journal of Climate 30, 6925–6943.

Ghorbanzadeh, O., Valizadeh Kamran, K., Blaschke, T., Aryal, J., Naboureh, A., Einali, J., Bian, J., 2019. Spatial prediction of wildfire susceptibility using field survey gps data and machine learning approaches. Fire 2. URL: https://www.mdpi.com/2571-6255/2/3/43, doi:10.3390/fire2030043.

Giannakidou, S., Radoglou-Grammatikis, P., Koussouris, S., Pertselakis, M., Kanakaris, N., Lekidis, A., Kaltakis, K., Koidou, M.P., Metallidou, C., Psannis, K.E., et al., 2022. 5g-enabled netapp for predictive maintenance in critical infrastructures, in: 2022 5th World Symposium on Communication Engineering (WSCE), IEEE. pp. 129–132.

Giglio, E., Randerson, L., van der Werf, J., 2015. Global forest fire emissions database (globfires). Earth System Science Data .

Gigović, L., Pourghasemi, H.R., Drobnjak, S., Bai, S., 2019. Testing a new ensemble model based on svm and random forest in forest fire susceptibility assessment and its mapping in serbia's tara national park. Forests 10. doi:10.3390/f10050408.

Gourley, J.J., Tabary, P., du Chatelet, J.P., 2006. Data quality of the meteo-france c-band polarimetric radar. Journal of Atmospheric and Oceanic Technology 23, 1340 – 1356. doi:10.1175/JTECH1912.1.

Grant, G.E., Beschta, R.L., 1996. Soil erosion and sediment yield following wildfire in the western usa. Catena 26, 1–18.

Grizelle, V.B.A.G.W.M.C.K.A.H.Q.M.F.S.A.N.M.J.G., 2018. Fire weather and likelihood: characterizing climate space for fire occurrence and extent in puerto rico. Climatic Change 146. URL: https://doi.org/10.1007/s10584-017-2045-6, doi:10.1007/s10584-017-2045-6.

Hayasaka, H., Skinner, C.N., 2008. 2008 forest fires in the northern california, usa. International Journal of Wildland Fire .

Hodges, J., Lattimer, B., 2019. Wildland fire spread modeling using convolutional neural networks. Fire Technology 55. doi:10.1007/s10694-019-00846-4.

Holm, S.M., Miller, M.D., Balmes, J.R., 2021. Health effects of wildfire smoke in children and public health tools: a narrative review. Journal of Exposure Science & Environmental Epidemiology 31, 1–20. URL: https://doi.org/10.1038/s41370-020-00267-4, doi:10.1038/s41370-020-00267-4. sN: 1559-064X.

Huo, W., Li, W., Zhang, Z., Sun, C., Zhou, F., Gong, G., 2021. Performance prediction of proton-exchange membrane fuel cell based on convolutional neural network and random forest feature selection. Energy Conversion and Management 243, 114367. URL: https://www.sciencedirect.com/science/article/pii/S0196890421005434, doi:https://doi.org/10.1016/j.enconman.2021.114367.

Julian, K.D., Kochenderfer, M.J., 2018. Distributed wildfire surveillance with autonomous aircraft using deep reinforcement learning. CoRR abs/1810.04244. URL: http://arxiv.org/abs/1810.04244, arXiv:1810.04244.

Juvanhol, R., Fiedler, N., SANTOS, A., Silva, G.F., OMENA, M., Eugenio, F., PINHEIRO, C., Ferraz Filho, A., 2021. Gis and fuzzy logic applied to modelling forest fire risk. Anais da Academia Brasileira de Ciências 93. doi:10.1590/0001-3765202120190726.

Kalogerakis, G., Papagiannaki, A., Karantzalos, K., 2015. Optical and infrared sensors for forest fire detection: A review. Journal of Applied Remote Sensing 9, 096122. doi:10.1117/1.JRS.9.096122.

Kam, M., Balch, J.K., Spies, T.A., 2016. Modeling wildfire susceptibility using random forests and maxent: A comparative study. Remote Sensing 8, 651–672.

Kathleen, H., Patrick, T., Tanja, S., Michael, F., 2021. Wind turbines and weather radar at deutscher wetterdienst, in: 2021 Kleinheubach Conference, pp. 1–1. doi:10.23919/IEEECONF54431.2021.9598441.

Keeley, J.E., Fotheringham, C.J., 2000. Wildfire management: paradigms past and present. Bioscience 50, 795–805.

Keeley, J.E., Safford, H., Fotheringham, C., Franklin, J., Moritz, M., 2009. The 2007 southern california wildfires: Lessons in complexity. Journal of Forestry 107, 287–296. URL: http://pubs.er.usgs.gov/publication/70036938.

Kennedy, R.A., Feddema, J.A., McRoberts, R.A., 2013. Remote sensing of wildfires: Progress, challenges, and opportunities. Remote Sensing of Environment 132, 1–22.

Kennedy, R.A., McRoberts, R.A., 2009. Mapping wildfire perimeters using remote sensing data. International Journal of Wildland Fire 18, 467–481.

Keys, P.W., DeBenedictis, J.A., 1998. Firefighters in the wildland-urban interface: A study of attitudes, beliefs, and behaviors. Fire Management Today 58, 24–31.

Khakzad, N., 2019. Modeling wildfire spread in wildland-industrial interfaces using dynamic bayesian network. Reliability Engineering & System Safety 189, 165–176. URL: https://www.sciencedirect.com/science/article/pii/S0951832018313887, doi:https://doi.org/10.1016/j.ress.2019.04.006.

Khvostikov, S., Bartalev, S., 2021. Use of remote sensing data in wildfire modelling. Sovremennye problemy distantsionnogo zondirovaniya Zemli iz kosmosa 18, 9–27. doi:10.21046/2070-7401-2021-18-5-9-27.

Klare, B.T., Ledford, J., 2018. The role of human behavior in the likelihood of wildfires in the united states. Journal of Forestry 116, 45–52.

Koo, T., Li, J., 2020. Automated wildfire detection using remote sensing and machine learning: A review. Remote Sensing 12, 2478–2505.

Koutsias, N., et al., 2005. An overview of fire behavior prediction models. Environmental Modelling & Software 20, 3–15.

Kozik, V., Nezhevenko, E., Feoktistov, A., 2014. Studying the method of adaptive prediction of forest fire evolution on the basis of recurrent neural networks. Optoelectronics, Instrumentation and Data Processing 50, 395–401. doi:10.3103/S8756699014040116.

Krawchuk, M.A., Moritz, M.A., Anderson, R.G., 2011. Fuel characteristics and fire regimes in north american forests: how will they change over the next few decades? Environmental Reviews 19, 269–280.

Krawchuk, M.A., Moritz, M.A., Parisien, M.A., 2009. A comparative analysis of methods for mapping fire regimes: Examples from the boreal forests of canada. Landscape Ecology 24, 967–981.

Lal, R., 2002. Soil erosion and the global carbon budget. Environment International 28, 189–200.

Lasaponara, R., Lanorte, A., 2007. Remotely sensed characterization of forest fuel types by using satellite aster data. International Journal of Applied Earth Observation and Geoinformation 9, 225–234. URL: https://www.sciencedirect.com/science/article/pii/S0303243406000353, doi:https://doi.org/10.1016/j.jag.2006.08.001.

Lawson, B., Armitage, B., 2008. Weather guide canadian forest fire danger rating system. Forest Fires .

Lee, J.J., Park, S.H., Kim, S., 2018. Simulating smoke dispersion and air quality impacts of forest fires in south korea using a numerical atmospheric model. Atmospheric Environment 178, 299–310.

Leithead, C., Gaffney, O., Tawn, J.A., Beniston, M., 2020. The role of social and environmental factors in the likelihood of wildfires in the western united states. Regional Environmental Change 20, 871–881.

Li, J., Ge, X., He, Q., Abbas, A., 2021. Aerosol optical depth (aod): spatial and temporal variations and association with meteorological covariates in taklimakan desert, china. PeerJ 9, e10542. doi:10.7717/peerj.10542.

Li, J., Koo, T., 2019. Wildfire susceptibility mapping using machine learning algorithms. International Journal of Wildland Fire 28, 669–683.

Li, J., Koo, T., 2021. Fire severity mapping with remote sensing and machine learning: A review. Remote Sensing 13, 1730–1758.

Li, L., Chown, D., Strand, M., 2020a. A machine learning approach to modeling fire regime responses to climate change in yosemite national park. Ecosphere 11, e03007.

Li, S., Wen, J., Wang, J., Liu, W., Yuan, S., 2022. A high-precision surrogate modeling method based on parallel multipoint expected improvement point infill criteria for complex simulation problems. Mathematics 10. URL: https://www.mdpi.com/2227-7390/10/17/3088, doi:10.3390/math10173088.

Li, X., Chen, Z., Wu, Q.M.J., Liu, C., 2020b. 3d parallel fully convolutional networks for real-time video wildfire smoke detection. IEEE Transactions on Circuits and Systems for Video Technology 30, 89–103. doi:10.1109/TCSVT.2018.2889193.

Li, X., Zhang, Y., Du, J., 2016. Machine learning algorithms for remote sensing data-based fire detection: A review. International Journal of Remote Sensing 37, 3545–3568.

Li, Y., Meng, X., Wan, H., 2010. A new control and decision idea on the ship fire hazard, in: 2014 Sixth International Conference on Measuring Technology and Mechatronics Automation, IEEE Computer Society, Los Alamitos, CA, USA. pp. 173–176. URL: https://doi.ieeecomputersociety.org/10.1109/ICMTMA.2010.375, doi:10.1109/ICMTMA.2010.375.

Linn, R., Reisner, J., Coleman, J., SMITH, S., 2002. Studying wildfire behavior using firetec. International Journal of Wildland Fire 11. doi:10.1071/WF02007.

Loehman, R.A., Keane, R.E., Holsinger, L.M., 2020. Simulation modeling of complex climate, wildfire, and vegetation dynamics to address wicked problems in land management. Frontiers in Forests and Global Change 3. URL: https://www.frontiersin.org/articles/10.3389/ffgc.2020.00003, doi:10.3389/ffgc.2020.00003.

Lozhkin, V., Tarkhov, D., Timofeev, V., Lozhkina, O., Vasilyev, A., 2016. Differential neural network approach in information process for prediction of roadside air pollution by peat fire. IOP Conference Series: Materials Science and Engineering 158, 012063. URL: https://dx.doi.org/10.1088/1757-899X/158/1/012063, doi:10.1088/1757-899X/158/1/012063.

Lu, Y., Wei, L., Kim, J., Ding, Y., 2021. Using machine learning techniques to predict the future distribution of the woodpecker under climate change. Science of The Total Environment 797, 144591. doi:10.1016/j.scitotenv.2021.144591.

Lutes, D.C., Keane, R.E., Caratti, J.F., Key, C.H., Benson, N.C., Sutherland, S., Gangi, L.J., 2006. FIREMON: Fire effects monitoring and inventory system. Technical Report. USDA. URL: https://doi.org/10.2737%2Frmrs-gtr-164, doi:10.2737/rmrs-gtr-164.

López Serrano, P., López-Sánchez, C., Álvarez González, J., García-Gutiérrez, J., 2016. A comparison of machine learning techniques applied to landsat-5 tm spectral data for biomass estimation. Canadian journal of remote sensing 42, 690–705. doi:10.1080/07038992.2016.1217485.

Makridakis, S., 2017. The forthcoming artificial intelligence (ai) revolution: Its impact on society and firms. Futures 90, 46–60. URL: https://www.sciencedirect.com/science/article/pii/S0016328717300046, doi:https://doi.org/10.1016/j.futures.2017.03.006.

Malamud, B.D., Turcotte, D.L., Rinaldo, A., 2010. A framework for evaluating forest fire detection systems. Environmental Modelling & Software .

Mallinis, G., Maris, F., Kalinderis, I., Koutsias, N., 2009. Assessment of post-fire soil erosion risk in fire-affected watersheds using remote sensing and gis. GIScience & Remote Sensing 46, 388–410. doi:10.2747/1548-1603.46.4.388.

Mario Miguel Valero, Lluís Jofre, R.T., 2021. Multifidelity prediction in wildfire spread simulation: Modeling, uncertainty quantification and sensitivity analysis. Environmental Modelling & Software 141, 105050. URL: https://www.sciencedirect.com/science/article/pii/S1364815221000931, doi:https://doi.org/10.1016/j.envsoft.2021.105050.

Markuzon, N., Kolitz, S., 2009. Data driven approach to estimating fire danger from satellite images and weather information, in: 2009 IEEE Applied Imagery Pattern Recognition Workshop (AIPR 2009), pp. 1–7. doi:10.1109/AIPR.2009.5466309.

Martín, Y., Zúñiga-Antón, M., Mimbrero, M.R., 2019. Modelling temporal variation of fire-occurrence towards the dynamic prediction of human wildfire ignition danger in northeast spain. Geomatics, Natural Hazards and Risk 10, 385–411. URL: https://doi.org/10.1080/19475705.2018.1526219, doi:10.1080/19475705.2018.1526219, arXiv:https://doi.org/10.1080/19475705.2018.1526219.

McGregor, S., Houtman, R., Montgomery, C., Metoyer, R., Dietterich, T.G., 2017. Fast optimization of wildfire suppression policies with smac. URL: https://arxiv.org/abs/1703.09391, doi:10.48550/ARXIV.1703.09391.

McWethy, D., et al., 2010. Human impact on fire regimes in western north america. BioScience 60, 603–608.

Mejia, N.N.B.H.T.B.M.K.J., 2018. Impact of the north american monsoon on wildfire activity in the southwest united states. International Journal of Climatology 39. doi:10.1002/joc.5899.

Mills, J.A., 2010. A historical review of fire weather research and forecast operations in the united states. Weather and Forecasting 25, 891–907. doi:10.1175/2010WAF2222438.1.

Mirabelli-Montan, Y., Marangon, M., Graça, A., Marangon, C., Wilkinson, K., 2021. A review of the techniques for mitigating the effects of smoke taint in wine production: Sourced from the article "techniques for mitigating the effects of smoke taint while maintaining quality in wine production: A review" (molecules, 2021). original language of the article: English. IVES Technical Reviews, vine and wine doi:10.20870/IVES-TR.2021.4846.

Montesinos López, O.A., Montesinos López, A., Crossa, J., 2022. Overfitting, model tuning, and evaluation of prediction performance. doi:10.1007/978-3-030-89010-0_4.

Moreno, A., Elías, J.A., Moreno, J.M., 2002. Wildfire effects on soil properties and erosion in a mediterranean environment. Catena 48, 103–115.

Moritz, M.A., Parisien, M.A., Batllori, E., Krawchuk, M.A., Van Dorn, J., Ganz, D.J., Hayhoe, K., 2012. Climate change and disruptions to global fire activity. Ecosphere 3, art49. URL: https://esajournals.onlinelibrary.wiley.com/doi/abs/10.1890/ES11-00345.1, doi:https://doi.org/10.1890/ES11-00345.1, arXiv:https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1890/ES11-00345.1.

Murphy, B.R., 1995. The relationships between fire and society: A review of the literature. International Journal of Wildland Fire 5, 201–208.

Nazaryan, H., McCormick, M.P., Menzel, W.P., 2008. Global characterization of cirrus clouds using calipso data. Journal of Geophysical Research: Atmospheres doi:10.1029/2007JD009481. aerosol and Clouds, Free Access.

Niamir, A., Baker, T., 2017. A comparative analysis of fire occurrence models in the United States. Forest Science 63, 720–732.

Niamir, A., Niamir-Fuller, M., 1999. Remote sensing and gis in predictive models of forest fires caused by lightning. International Journal of Wildland Fire 9, 1–10.

Oceanic, N., (NOAA), A.A., 2021. National weather service data and information. URL: https://www.weather.gov/obs/. online.

Olabarria, J., 2019. Strategic and tactical planning to improve suppression efforts against large forest fires in the catalonia region of spain. Forest Ecology and Management 432, 612–622. doi:10.1016/j.foreco.2018.09.039.

Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A., Pereira, J.M., 2012. Modeling spatial patterns of fire occurrence in mediterranean europe using multiple regression and random forest. Forest Ecology and Management 275, 117–129. URL: https://www.sciencedirect.com/science/article/pii/S0378112712001272, doi:https://doi.org/10.1016/j.foreco.2012.03.003.

O'Connor, C., Calkin, D., Thompson, M., 2017. An empirical machine learning method for predicting potential fire control locations for pre-fire planning and operational fire management. International Journal of Wildland Fire 26. doi:10.1071/WF16135.

Palaiologou, P., Kalabokidis, K., Day, M.A., Ager, A.A., Galatsidas, S., Papalampros, L., 2022. Modelling fire behavior to assess community exposure in europe: Combining open data and geospatial analysis. ISPRS International Journal of Geo-Information 11. URL: https://www.mdpi.com/2220-9964/11/3/198, doi:10.3390/ijgi11030198.

Papagiannaki, A., Kalogerakis, G., Karantzalos, K., 2018. A review of remote sensing techniques for forest fire detection and monitoring. Remote Sensing .

Parisien, M.A., Moritz, M.A., 2009. Environmental controls on the distribution of wildfire at multiple spatial scales. Ecological Monographs 79, 127–154. URL: http://www.jstor.org/stable/27646169.

Parks, S., Holsinger, L., Panunto, M., Jolly, W., Dobrowski, S., Dillon, G., 2018. High-severity fire: Evaluating its key drivers and mapping its probability across western us forests. Environmental Research Letters

13. doi:10.1088/1748-9326/aab791.

Penman, T., Nicholson, A., Bradstock, R., Collins, L., Penman, S., Price, O., 2015. Reducing the risk of house loss due to wildfires. Environmental Modelling and Software 67, 12–25. URL: https://www.sciencedirect.com/science/article/pii/S1364815214003776, doi:https://doi.org/10.1016/j.envsoft.2014.12.020.

Pereira, A.A., Pereira, J.M.C., Libonati, R., Oom, D., Setzer, A.W., Morelli, F., Machado-Silva, F., De Carvalho, L.M.T., 2017. Burned area mapping in the brazilian savanna using a one-class support vector machine trained by active fires. Remote Sensing 9. URL: https://www.mdpi.com/2072-4292/9/11/1161, doi:10.3390/rs9111161.

Pereira, J., Mendes, J., Júnior, J.S.S., Viegas, C., Paulo, J.R., 2022. A review of genetic algorithm approaches for wildfire spread prediction calibration. Mathematics 10. URL: https://www.mdpi.com/2227-7390/10/3/300, doi:10.3390/math10030300.

Perona, A.J.R., Radeva, P.D., 2019. Real-time wildfire detection using thermal cameras and machine learning. Journal of Real-Time Image Processing 14, 437–450.

Phan, T.C., Nguyen, T.T., 2019. Remote sensing meets deep learning: Exploiting spatio-temporal-spectral satellite images for early wildfire detection, in: Environmental Science, pp. 1–9.

Pierce, A.D., Farris, C.A., Taylor, A.H., 2012. Use of random forests for modeling and mapping forest canopy fuels for fire behavior analysis in lassen volcanic national park, california, usa. Forest Ecology and Management 279, 77–89. URL: https://www.sciencedirect.com/science/article/pii/S0378112712002654, doi:https://doi.org/10.1016/j.foreco.2012.05.010.

Pourtaghi, Z.S., Pourghasemi, H.R., Aretano, R., Semeraro, T., 2016. Investigation of general indicators influencing on forest fire and its susceptibility modeling using different data mining techniques. Ecological Indicators 64, 72–84. URL: https://www.sciencedirect.com/science/article/pii/S1470160X15007359, doi:https://doi.org/10.1016/j.ecolind.2015.12.030.

Prados, A.I., Kondragunta, S., Ciren, P., Knapp, K.R., 2007. Goes aerosol/smoke product (gasp) over north america: Comparisons to aeronet and modis observations. Journal of Geophysical Research: Atmospheres doi:10.1029/2006JD007968. aerosol and Clouds, Free Access.

Pu, R., Gong, P., 2004. Determination of burnt scars using logistic regression and neural network techniques from a single post-fire landsat 7 etm + image. Photogrammetric Engineering & Remote Sensing 70, 841–850. doi:10.14358/PERS.70.7.841.

Pyne, S.J., Goldammer, J.G., 1997. The culture of fire: An introduction to anthropogenic fire history, in: Clark, J.S., Cachier, H., Goldammer, J.G., Stocks, B. (Eds.), Sediment Records of Biomass Burning and Global Change, Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 71–114.

Radeloff, V.C., Hammer, R.B., Steward, B., Carter, N.H., Mladenoff, D.J., Stevens, M.R., 2006. Assessing the impact of human activity on wildland fire potential in the united states. Ecological Applications 16, 886–899.

Radke, D., Hessler, A., Ellsworth, D., 2019. Firecast: Leveraging deep learning to predict wildfire spread, in: Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, pp. 4575–4581. doi:10.24963/ijcai.2019/636.

Ramezani Ziarani, M., Bookhagen, B., Schmidt, T., Wickert, J., de la Torre, A., Hierro, R., 2019. Using convective available potential energy (cape) and dew-point temperature to characterize rainfall-extreme events in the south-central andes. Atmosphere 10. URL: https://www.mdpi.com/2073-4433/10/7/379, doi:10.3390/atmos10070379.

Reddy, K.R., Unknown. Soil and Water Conservation for Productivity and Environmental Protection. Google Books.

Reid, C., Jerrett, M., Petersen, M., Pfister, G., Morefield, P., Tager, I., Raffuse, S., Balmes, J., 2015. Spatiotemporal prediction of fine particulate matter during the 2008 northern california wildfires using machine learning. Environmental science and technology 49. doi:10.1021/es505846r.

Riaño, D., Ustin, S., Usero, L., Patricio, M.A., 2005. Estimation of fuel moisture content using neural networks, in: Artificial Intelligence and Knowledge Engineering Applications: A Bioinspired Approach, pp. 489–498. doi:10.1007/11499305_50.

Riley, K., Grenfell, I., Finney, M., Crookston, N., 2014. Utilizing random forests imputation of forest plot data for landscape-level wildfire analyses, in: USDA, pp. 1–8. doi:10.14195/978-989-26-0884-6_67.

Rodrigues, M., Alcasena, F., Vega-Garcia, C., 2019. Modeling initial attack success of wildfire suppression in catalonia, spain. Science of The Total Environment 666. doi:10.1016/j.scitotenv.2019.02.323.

Rosero, E.C., Rastogi, A., 2010. Watershed hydrology and water management in the aftermath of wildfires.

Ruffault, J., Mouillot, F., 2015. How a new fire-suppression policy can abruptly reshape the fire-weather relationship. Ecosphere 6, 199. doi:10.1890/ES15-00182.1.

Ryan, K.C., Rumker, D.A., 2001. Forest fires and the atmosphere. Journal of Geophysical Research: Atmospheres .

Salem, K., Barbara, D., Lipton, R., 1992. Probabilistic diagnosis of hot spots, in: 1992 Eighth International Conference on Data Engineering, IEEE Computer Society, Los Alamitos, CA, USA. pp. 30,31,32,33,34,35,36,37,38,39. doi:10.1109/ICDE.1992.213208.

Samadi, Wajizah, S., Munawar, A.A., 2020. Near infrared spectroscopy (nirs) data analysis for a rapid and simultaneous prediction of feed nutritive parameters. Data in Brief 29, 105211. URL: https://www.sciencedirect.com/science/article/pii/S2352340920301050, doi:https://doi.org/10.1016/j.dib.2020.105211.

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., Strobl, P., Liberta, G., Giovando, C., Boca, R., Sedano, F., Kempeneers, P., McInerney, D., Withmore, C., de Oliveira, S.S., Rodrigues, M., Durrant, T., Corti, P., Oehler, F., Vilar, L., Amatulli, G., 2012. Comprehensive monitoring of wildfires in europe: The european forest fire information system (effis), in: Tiefenbacher, J. (Ed.), Approaches to Managing Disaster. IntechOpen, Rijeka. chapter 5, pp. 1–25. URL: https://doi.org/10.5772/28441, doi:10.5772/28441.

Sayad, Y.O., Mousannif, H., Al Moatassime, H., 2019. Predictive modeling of wildfires: A new dataset and machine learning approach. Fire Safety Journal 104, 130–146. URL: https://www.sciencedirect.com/science/article/pii/S0379711218303941, doi:https://doi.org/10.1016/j.firesaf.2019.01.006.

Scheller, R., Kretchun, A., Hawbaker, T.J., Henne, P.D., 2019. A landscape model of variable social-ecological fire regimes. Ecological Modelling 401, 85–93. URL: https://www.sciencedirect.com/science/article/pii/S0304380019301279, doi:https://doi.org/10.1016/j.ecolmodel.2019.03.022.

Schoennagel T, Balch JK, B.S.H., 2017. Adapt to more wildfire in western north american forests as climate changes. Proceedings of the National Academy of Sciences 114, 4582–4590. doi:10.1073/pnas.1617464114.

She, L., Zhang, H., Wang, W., Wang, Y., Shi, Y., 2019. Evaluation of the multi-angle implementation of atmospheric correction (maiac) aerosol algorithm for himawari-8 data. Remote Sensing 11. URL: https://www.mdpi.com/2072-4292/11/23/2771, doi:10.3390/rs11232771.

Shi, G.X., Zhang, W.Q., Wang, G.B., Zhao, J., Chai, S.Z., Zhao, Z.Y., 2021. Timestamp-aligning and keyword-biasing end-to-end asr front-end for a kws system. EURASIP Journal on Audio, Speech, and Music Processing 2021. doi:10.1186/s13636-021-00212-9.

Smith, J.W., Huang, C., 2019. Wildfire risk assessment in the western united states: integrating social and biophysical factors. Natural Hazards 98, 647–662.

Stephens, S.L., 2015. Climate Change and Fire Management. Google Books. URL: https://books.google.com/books?id=U6fkCgAAQBAJ.

Su, X., Yan, Y., Zhang, H., 2017. Predictive models for fire spread behaviour using landsat data. International Journal of Remote Sensing 38, 1650–1664.

Subramanian, S., Crowley, M., 2017. Learning forest wildfire dynamics from satellite images using reinforcement learning, in: Sec. Environmental Informatics and Remote Sensing, pp. 1–5.

Sun, X., Long, Z., Jia, J., 2021. A multi-scale maxent approach to model habitat suitability for the giant pandas in the qionglai mountain, china. Global Ecology and Conservation 30, e01766. URL: https://www.sciencedirect.com/science/article/pii/S2351989421003164, doi:https://doi.org/10.1016/j.gecco.2021.e01766.

Szpakowski, D.M., Jensen, J.L.R., 2019. A review of the applications of remote sensing in fire ecology. Remote Sensing 11. URL: https://www.mdpi.com/2072-4292/11/22/2638, doi:10.3390/rs11222638.

Taylor, J., 2017. Fire Management Decision Support Systems: An Overview. John Wiley & Sons.

Tehrany, M., Jones, S., Shabani, F., Martínez-Álvarez, F., Bui, D., 2019. A novel ensemble modelling approach for the spatial prediction of tropical forest fire susceptibility using logitboost machine learning classifier and multi-source geospatial data. Theoretical and Applied Climatology doi:10.1007/s00704-018-2628-9.

Teixeira, C., de Freitas, J., de Almeida, L., de Souza, R., 2020. Wildfire preparedness and response through machine learning techniques: A review. Expert Systems with Applications 149, 113844.

Vacchiano, G., Foderi, C., Berretti, R., Marchi, E., Motta, R., 2018. Modeling anthropogenic and natural fire ignitions in an inner-alpine valley. Natural Hazards and Earth System Sciences 18, 935–948. URL: https://nhess.copernicus.org/articles/18/935/2018/, doi:10.5194/nhess-18-935-2018.

Van Wagner, C., 1987. Development and structure of the canadian forest fire weather index system. National Capital Region .

Vasconcelos, M., Silva, S., Tomé, M., Alvim, M., Pereira, J., 2001. Spatial prediction of fire ignition probabilities: Comparing logistic regression and neural networks. Photogrammetric Engineering and Remote Sensing 67, 73–81.

Vasilakos, C., Kalabokidis, K., Hatzopoulos, J., Kallos, G., Matsinos, Y., 2007. Integrating new methods and tools in fire danger rating. International Journal of Wildland Fire 16, 306–316. doi:10.1071/WF05091.

Vecín-Arias, D., Castedo-Dorado, F., Ordóñez, C., Rodríguez-Pérez, J.R., 2016. Biophysical and lightning characteristics drive lightning-induced fire occurrence in the central plateau of the iberian peninsula. Agricultural and Forest Meteorology 225, 36–47. URL: https://www.sciencedirect.com/science/article/pii/S0168192316302593, doi:https://doi.org/10.1016/j.agrformet.2016.05.003.

Vilar, L., Gómez, I., Martinez-Vega, J., Echavarría, P., Riaño, D., Martín, M., 2016. Multitemporal modelling of socio-economic wildfire drivers in central spain between the 1980s and the 2000s: Comparing generalized linear models to machine learning algorithms. PLOS ONE 11, e0161344. doi:10.1371/journal.pone.0161344.

Vos, J., 2017. Wildfire risk analysis and management: A review of modeling approaches. Natural Hazards 88, 1093–1114. URL: https://doi.org/10.1007/s11069-016-2658-y, doi:10.1007/s11069-016-2658-y.

Watson, G.L., Telesca, D., Reid, C.E., Pfister, G.G., Jerrett, M., 2019. Machine learning models accurately predict ozone exposure during wildfire events. Environmental Pollution 254, 112792. URL: https://www.sciencedirect.com/science/article/pii/S0269749119301733, doi:https://doi.org/10.1016/j.envpol.2019.06.088.

Yao, J., Brauer, M., Raffuse, S.M., Henderson, S.B., 2018a. Machine learning approach to estimate hourly exposure to fine particulate matter for urban, rural, and remote populations during wildfire seasons. Environmental science and technology 52 22, 13239–13249.

Yao, J., Raffuse, S.M., Brauer, M., Williamson, G.J., Bowman, D.M., Johnston, F.H., Henderson, S.B., 2018b. Predicting the minimum height of forest fire smoke within the atmosphere using machine learning and data from the calipso satellite. Remote Sensing of Environment 206, 98–106. URL: https://www.sciencedirect.com/science/article/pii/S003442571730603X, doi:https://doi.org/10.1016/j.rse.2017.12.027.

Yongsheng, Liu, Yansong, Yang, Chang, Yu, Gu, 2015. Forest fire detection using artificial neural network algorithm implemented in wireless sensor networks, in: ZTE Communications, pp. 16–68.

Young, A.M., Higuera, P.E., Duffy, P.A., Hu, F.S., 2017. Climatic thresholds shape northern high-latitude fire regimes and imply vulnerability to future climate change. Ecography 40, 606–617. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.02205, doi:https://doi.org/10.1111/ecog.02205, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.02205.

Zammit, O., Descombes, X., Zerubia, J., 2006. Burnt area mapping using support vector machines. Forest Ecology and Management - FOREST ECOL MANAGE 234. doi:10.1016/j.foreco.2006.08.269.

Zhang, G., Wang, M., Liu, K., 2019. Forest fire susceptibility modeling using a convolutional neural network for yunnan province of china. International Journal of Disaster Risk Science 10. doi:10.1007/s13753-019-00233-1.

Zhang, G., Wang, M., Liu, K., 2021. Deep neural networks for global wildfire susceptibility modelling. Ecological Indicators 127, 107735. URL: https://www.sciencedirect.com/science/article/pii/S1470160X21004003, doi:https://doi.org/10.1016/j.ecolind.2021.107735.

Zhang, P., Patuwo, E., Hu, M., 1998. Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting 14, 35–62. doi:10.1016/S0169-2070(97)00044-7.

xing Zhang, Q., hua Lin, G., ming Zhang, Y., Xu, G., jun Wang, J., 2018. Wildland forest fire smoke detection based on faster r-cnn using synthetic smoke images. Procedia Engineering 211, 441–446. URL: https://www.sciencedirect.com/science/article/pii/S1877705817362574, doi:https://doi.org/10.1016/j.proeng.2017.12.034. 2017 8th International Conference on Fire Science and Fire Protection Engineering (ICFSFPE 2017).

Zhao, Y., Ma, J., Li, X., Zhang, J., 2018. Saliency detection and deep learning-based wildfire identification in uav imagery. Sensors 18, 712. doi:10.3390/s18030712.

Zheng, Z., Huang, W., Li, S., Zeng, Y., 2017. Forest fire spread simulating model using cellular automaton with extreme learning machine. Ecological Modelling 348, 33–43. URL: https://www.sciencedirect.com/science/article/pii/S0304380016303064, doi:https://doi.org/10.1016/j.ecolmodel.2016.12.022.

Zou, Y., O'Neill, S.M., Larkin, N.K., Alvarado, E.C., Solomon, R., Mass, C., Liu, Y., Odman, M.T., Shen, H., 2019. Machine learning-based integration of high-resolution wildfire smoke simulations and observations for regional health impact assessment. International Journal of Environmental Research and Public Health 16. URL: https://www.mdpi.com/1660-4601/16/12/2137, doi:10.3390/ijerph16122137.