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Review

Bushfire Management Strategies: Current Practice, Technological Advancement and Challenges

Sahan Bandara [1], Satheeskumar Navaratnam [2,*] and Pathmanathan Rajeev [3]

1 Department of Civil Engineering, University of Peradeniya, Peradeniya 20400, Sri Lanka; sahan@eng.pdn.ac.lk
2 School of Engineering, RMIT University, 124 La Trobe Street, Melbourne, VIC 3000, Australia
3 Department of Civil & Construction Engineering, Swinburne University of Technology, Melbourne, VIC 3122, Australia; prajeev@swin.edu.au
* Correspondence: sathees.nava@rmit.edu.au

Abstract: Bushfires are classified as catastrophic disasters capable of inflicting significant destruction. The key detrimental consequences of bushfires include the loss of human lives, trauma within communities, economic losses and environmental damage. For example, the estimated economic loss from the September 2019 to March 2020 bushfires in New South Wales (Australia) was about AUD 110 billion, including more than 3000 burned houses. There has been a notable increase in both the frequency and intensity of bushfires, as clearly demonstrated by recent bushfire events. Bushfires are an intricate phenomenon that transpires across various spatial and temporal scales. Further, the changing circumstances of landscapes, vegetation patterns, weather conditions and ecosystems account for the complexity. Therefore, continual attention is essential for the development of bushfire management strategies. In this context, this paper undertakes a comprehensive literature review of bushfire management strategies, encompassing aspects such as bushfire prediction, detection, suppression and prevention. Based on the review, a bushfire management framework is proposed that can eliminate or successfully mitigate the consequences of bushfires. Further, the paper delves into the domains of fire weather conditions, the initiation of bushfires and the adverse consequences stemming from these fires. Both terrestrial and aerial remote sensing methods have proven to be effective in predicting and detecting bushfires. Nevertheless, a simple unique solution cannot be proposed for bushfire management. Changing weather conditions, topography and the geographic mix of asset types need to be considered when deciding on bushfire management strategies and their breadth and depth of application.

Keywords: bushfire; prediction; detection; management; economic loss; fire weather

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1. Introduction

Bushfire, also known as wildfire, forest fire and unplanned fire, is one of the catastrophic disasters caused by natural causes or human activities that occur in most countries around the world [1]. These events can pose severe destruction to human and animal lives, infrastructure, biodiversity and the environment [2,3]. Examples of the occurrence of worldwide fires can be found in different countries such as Australia [4,5], Canada [6], the United States [7], China [8], South Africa [9], Greece [10], Portugal [11] and Brazil [12]. Among these countries, Australia has been more susceptible to bushfires over the past decades, considering its topography, vegetation patterns and bushfire-prone weather conditions [13,14]. The most recent severe bushfire events in New South Wales, Australia, extended from September 2019 to March 2020, resulting in 34 fatalities and an estimated amount of AUD 110 billion in economic loss, including 3000 burned houses [15,16]. The highest number of fatalities from a bushfire in Australia was recorded on Saturday 7th, February 2009 (Black Saturday) in the state of Victoria, in which 173 people lost their lives. There were extreme weather conditions on this day such as temperatures reaching 46.4 °C and winds gusting up to 100 km/h, which initiated major fires in 14 geographical regions, and the total burnt area was more than 350,000 hectares [4,17]. The degree of destruction caused by bushfires is evident from the long line of events of Australian bushfires over the centuries, and controlling widespread bushfires become increasingly challenging, specifically due to the upsurge in bushfire-prone weather conditions [18].

Bushfire management is a crucial aspect that researchers have investigated comprehensively to understand the causes and subsequently to mitigate or minimise the catastrophes caused by devastating bushfires (e.g., [19–21]). A bushfire management system plays an essential role in controlling bushfires and associated losses to life and the economy while preserving the environment and biodiversity. Some of the key steps in a bushfire management system are prediction, detection, suppression and prevention of bushfires. Prediction refers to forecasting or estimating the bushfire occurrences, fire risk and fire behaviour such as rate of fire spread, intensity, flame length and angle, using climatic, environmental and geospatial data which change over time [22,23]. This sort of bushfire prediction model is often complex and computationally expensive since most input data change with time and space, requiring separate simulations for different geographic extents with different spatial resolutions [24]. Bushfire risk is most often defined in terms of "fire danger", and fire danger is quantified by defining different indices: wind speed, fuel type, fuel moisture content, relative humidity, air temperature and precipitation. Bushfire prediction can be from satellite imagery-based remote sensing techniques and scanning-based techniques. Satellite imagery can be employed as a quick and reliable technique for identifying fuel characteristics and bushfire susceptibility mapping [25]. However, satellite imagery has a lower temporal resolution than its excellent spatial resolution, particularly with Earth-orbiting satellites. Further, it can be challenging to mitigate the impacts of smoke and identify details in the forest understory when using this method [26]. Satellite imagery and scanning-based techniques often accompany advanced image processing techniques such as super-resolution mapping and generative adversarial network schemes (e.g., [27,28]).

Bushfire detection is of paramount importance in a bushfire management system since it determines the initial attack delay, which is the response time for the bushfire suppression resources to arrive at the fire ground [29]. Suppose the bushfire detection techniques are robust enough to detect a bushfire quickly just after initiation. In that case, there are better chances of the fire being contained before it turns out to be a widespread fire causing significant damage. Conventional bushfire detection techniques include smoke detectors, watch towers, satellite images, wireless sensor networks and remotely operated vehicles [21]. Images from satellites and remotely operated vehicles are analysed to detect flagging pixels representing the potential of bushfires. On the other hand, smoke sensors and temperature sensors in wireless sensor networks indicate the generation of smoke and rise in temperature, which may indicate potential bushfires. In addition to these typical techniques, using unmanned aerial vehicles for bushfire detection and using artificial intelligence for data processing have been extensively investigated as emerging techniques that possess improved reliability and reduced cost (e.g., [30,31]). Further, the subjectivity and human error involved with conventional detection techniques can be eliminated via employing automated data processing algorithms [30]. Furthermore, relying solely on human observers to monitor vast forested areas is unfeasible. The main drawback of wireless sensor network-based bushfire detection is the economic burden of installing sensors across wide forests. Unlike terrestrially deployed systems, satellite imagery can cover very large areas [32]. However, the operational cost of satellites and the required technical competence is high compared to other techniques. Moreover, some satellite imagery's temporal and spatial resolution is low, which can negatively affect the detection accuracy.

Bushfire suppression is generally carried out by direct techniques where treatment is directly applied to burning fuel, such as wetting and chemical quenching [33]. Indirect techniques of bushfire suppression include fuel reduction, contingency fire lines and indirect fire lines. Different aspects of bushfire suppression have been explored by researchers such as modelling aspects [34], economic aspects [35] and aerial suppression aspects [36].

The ultimate goals of any bushfire management system are to control fuels and thereby the fire regimes, increase the infrastructure's resistance to fires and achieve a quick recovery after a devastating bushfire event while promoting adaptation [37].

The only possible solution to address the issue of bushfires is to minimise its effects by making all the potential efforts to achieve the best possible outcomes. In this regard, bushfire management is of paramount importance. This paper aims to conduct a comprehensive review of the literature on bushfire management strategies, providing a specific focus on bushfire detection techniques. Under the topic of bushfire management, this paper reviews the existing literature on bushfire prediction, detection, suppression and prevention techniques, highlighting the advantages and disadvantages of different approaches. By identifying the advantages and limitations of different bushfire management strategies, this paper motivates further research on this timely topic of bushfire management and a bushfire management framework is proposed to guide the decision-making process to control the initiation and spread of bushfires effectively. The paper is structured as follows. Section 2 provides the methodology for the literature review, highlighting how papers were selected based on keywords. A comprehensive description of fire weather conditions and bushfire initiation is provided in Section 3. The adverse effects of bushfires are presented in Section 4, considering economic, environmental and social aspects. Section 5 discusses bushfire management strategies, specifically focusing on bushfire detection techniques. Conclusions are drawn and presented in the final section of the paper.

2. Methodology for Literature Review

A thorough literature review was undertaken, focusing on state-of-the-art techniques in bushfire detection and management, using peer-reviewed journal articles and other publications. The Web of Science (WoS) database was utilised for conducting a bibliometric analysis, and the search string used in this analysis consisted of four keywords such as "Bushfire", "Management"," Prediction" and "Economy". To explore and identify various trends and occurrences of keywords within the literature, VOSviewer software (v.1.6.18) was employed. A total of 2000 journal articles spanning the years 1990 to 2023 were selected from WoS. Subsequently, a network visualisation diagram illustrating keyword co-occurrences was generated using VoSviewer, as depicted in Figure 1. Different labels are employed within this network visualisation diagram, and the size of each label (circle) corresponds to the frequency of co-occurrences for that item. Larger labels indicate a higher number of co-occurrences associated with the item. Additionally, the coloration of each item signifies its membership in distinct clusters. The analysis encompasses a total of 449 items distributed across eight different clusters, interconnected by a total of 8254 links. Based on the network visualisation displayed below, prominent keywords within the context include fire management, climate change, biodiversity, forest conservation, resilience, prediction and identification. These keywords signify the most extensively studied topics. Numerous additional keywords are connected to these primary keywords within the network. Research articles highly relevant to the aforementioned keywords and the scope of this study were selected from the WOS database and utilised for the comprehensive review. Additionally, the reference list of each article was screened to identify any potentially relevant articles that may have been overlooked. Finally, the selected articles were sorted into categories considering the subsections of this paper, such as fire weather conditions and bushfire initiation, adverse effects of bushfires and bushfire management strategies. Fire weather conditions and bushfire initiation are described in Section 3, which consists of a summary of 21 relevant studies, whereas the adverse effects of bushfires explained in Section 4 consists of a review of 18 studies. The bushfire management component, which is in Section 5, provides a comprehensive review of 93 studies. A summary of the papers highlighting the above information is presented in the following sections.

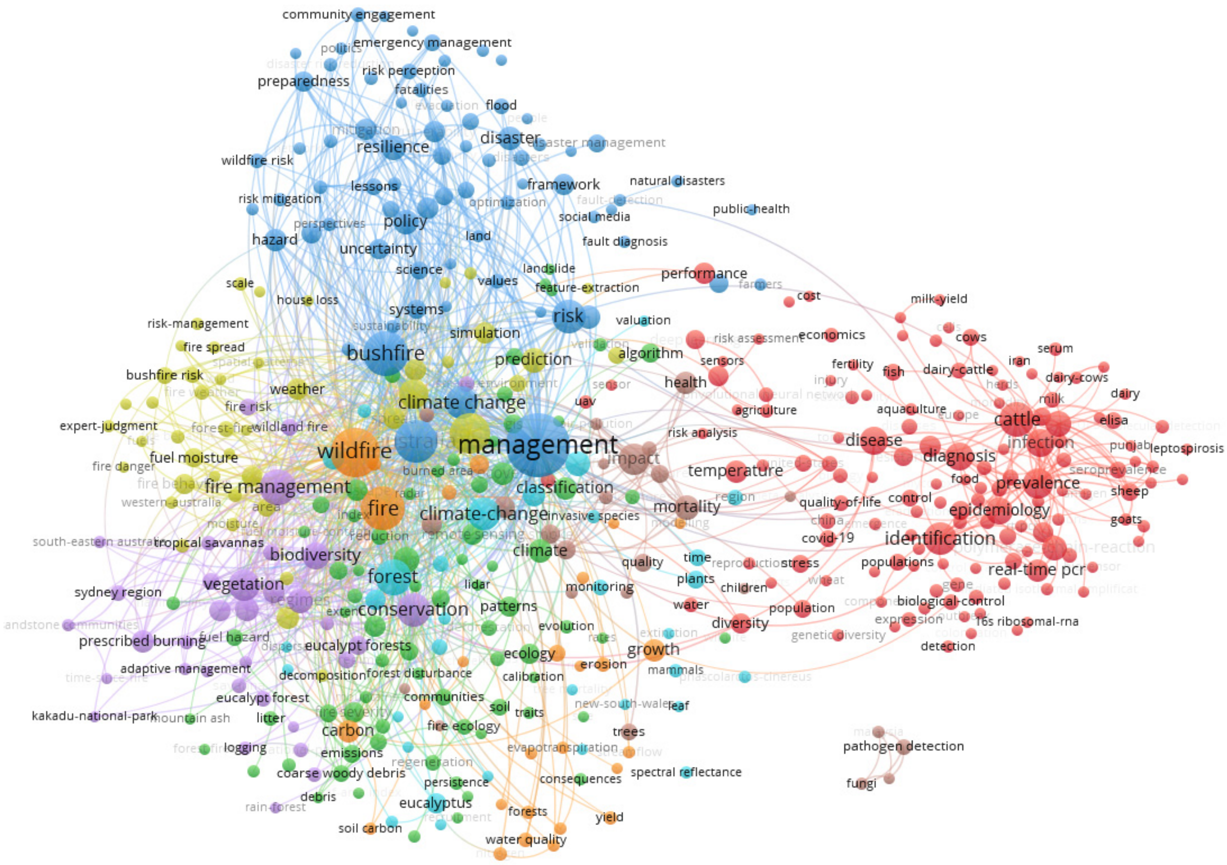

Figure 1. Network visualisation diagram of co-occurrence of keywords.

3. Fire Weather Conditions and Bushfire Initiation

There is a wide array of causes for bushfire initiation, as illustrated in Figure 2. Some causes are inevitable natural events like lightning [38,39]. A slight spark in extreme weather conditions and elevated temperature can initiate a spot fire, which can become a widespread large-scale bushfire when combined with higher wind speeds. The amount of rainfall and temperature preceding a bushfire also play a vital role in determining the spread of fire. Compared to other parts of the world, Australia is more susceptible to fire weather conditions, being the driest continent on earth [40]. Fire weather is generally expressed as a combination of relative humidity, wind speed, rainfall and air temperature [41]. A widely used empirical indicator for quantifying the weather conditions related to extreme bushfire scenarios and related suppression difficulties was developed in 1960, known as the MacArthur Forest Fire Danger Index (FFDI) [42]. The FFDI is defined as a function of air temperature, relative humidity, average wind speed and drought factor, a relative measure of fuel availability [41]. Elevated fire danger is present under severe drought in hot, dry, humid, windy conditions. Even though the FFDI can provide a reasonably accurate estimation of the bushfire danger for a considered region, this indicator does not account for fuel's physical texture and dryness [43,44]. The energy released in burning large fuel elements such as branches is significantly higher when compared to that of fine fuels, which is not accounted for in the FFDI. Further, the effect of heat waves on the dryness of fuel is not comprehensively considered in the FFDI [41]. Other than the FFDI, there are several indices that integrate different meteorological variables into a single indicator that reflects the fire danger, such as the Canadian Forest Fire Weather Index System (FWI) [45] and the United States National Fire Danger Rating System (NFDRS) [46]. A common observation reported around the world is global warming and the rise of mean temperatures ([47]). For example, the mean temperature in Australia has significantly increased over time, and some areas have experienced a 1.5–2 °C rise in mean temperature since 1960 [48]. It was reported that a record-setting heat wave was present a few days before the initiation of the devastating Black Saturday bushfires in Melbourne, where the city experienced three consecutive days of maximum temperature exceeding 43 °C [44]. In addition, preceding the Black Saturday bushfires, Melbourne had 35 days with no measurable rain, reported to be Melbourne's driest start of the year in more than 150 years [48]. Therefore, it is evident that fire weather conditions play a vital role in bushfire initiation and spread.

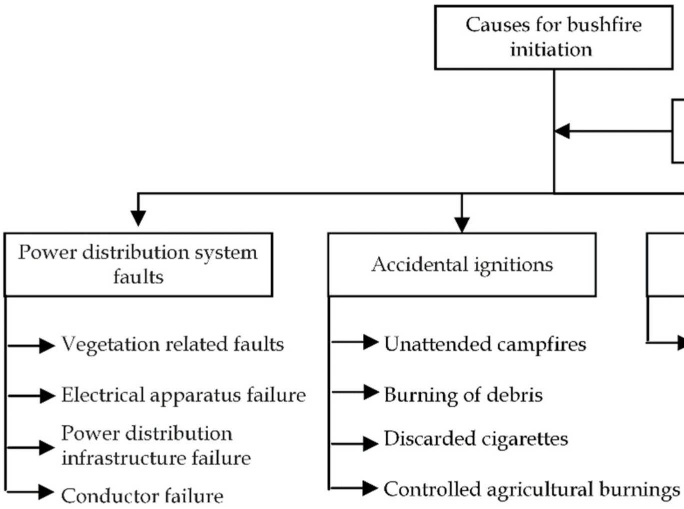

Figure 2. Causes for bushfire initiation.

Accidental ignition is another key factor for bushfire initiation [49]. Human errors and accidental ignitions are reported in the cases of unattended campfires, burning of debris and improperly discarded cigarettes [50]. Further, there is a risk arising from faulty agricultural machinery generating sparks leading to spot fires [51]. Another form of accidental ignition is controlled burning, which turns into unmanageable fires due to negligence or extreme fire weather conditions [52]. Even though controlled burning is a common agricultural practice that has evolved for centuries, it carries the inevitable risk of bushfire initiation [53]. In addition to accidental ignitions, power distribution system faults can be a root cause of fire initiation. Power distribution system faults can be broadly categorised into vegetation related faults, electrical apparatus failures, power distribution infrastructure failures and conductor failures [50]. In dry, hot, humid and windy conditions, sparks generated from a power distribution fault can ignite the biomass, initiating a fire. It is vital to monitor the structural health of power distribution systems to avoid potential faults, and power distribution infrastructure reaching the end of service life needs to be replaced [54–57]. A detailed investigation into the causes of the Black Saturday bushfires in Australia revealed that a power line brought down by high winds generated sparks that initiated the fire in the Kilmore East region, where 121 people were killed and approximately 100,000 ha burned in less than 12 h [2]. Deliberate acts of arson are also found to be a major cause for bushfire initiation identified by the fire agencies attending the bushfires [58,59]. The size, spread and duration of a bushfire initiated due to any of the aforementioned causes are determined by the fire weather conditions, which can result in large-scale, widespread, uncontrollable bushfires.

4. Adverse Effects of Bushfires

There are numerous adverse effects of bushfires, among which fatalities, injuries and trauma on bushfire-susceptible communities can be considered as the worst social outcomes [3,60]. The actual cause of death during a bushfire has been explored, and the main causes are identified as burnings from flames and heat, smoke inhalation, heart attack, over-exertion and falling tree limbs [3]. Human behaviour and decision-making during an event of bushfire determine survival, while bushfire awareness dominates the capacity to respond. Late evacuations, defending properties from bushfires, returning into burning buildings to rescue people and waiting to be rescued most often increase the number of fatalities [3]. Figure 3 illustrates a summary of the effects of bushfires, and these are broadly categorised into three groups such as economic, environmental and social.

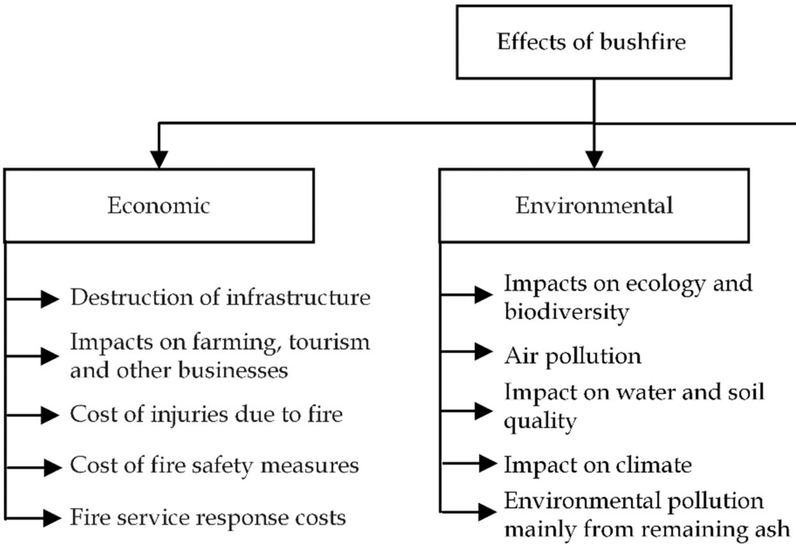

Figure 3. Effects of bushfire.

The economic effects of bushfires can be subdivided into cost in anticipation, cost as a consequence and cost in response [18]. Cost in anticipation refers to the cost of fire safety measures, fire safety education and training, maintenance of fire safety equipment and fire research. Cost as a consequence is from the property losses, cost of injury due to fire and loss of businesses such as tourism and farming. Fire service response costs and justice costs can be categorised as costs incurred in response [50]. Detailed investigations about the causes and effects of bushfires have estimated the economic loss of large-scale bushfire events. The estimated economic loss of the September 2019 to March 2020 bushfires in New South Wales (Australia) was about AUD 110 billion, that of the June 2017 bushfire in Pedrogao Grande (Portugal) was about EUR 500 million, and that of the 1939 January bushfires in Victoria and New South Wales (Australia) was about AUD 750 million [2,17,61]. A comprehensive summary of the economic losses and fatalities caused by major events of wildfires can be found in the authors' previous work [50]. These numbers represent the implications of widespread, large-scale bushfires on the economy of a country.

Fire regime (fire spread pattern, intensity, severity and frequency) and the smoke generated from bushfires can have significant effects on the environment [62]. Figure 4 illustrates some of the adverse effects of bushfires. Air pollution caused by smoke and hazardous gas emissions affects the global atmospheric composition while having adverse effects on human and animal health [63,64]. Respiratory morbidity is often associated with bushfire smoke, whereas the particulate matter in smoke has the potential to trigger acute coronary events such as heart attacks [65]. In addition, an increase in the concentration of carbon dioxide due to the emissions from bushfires can affect the atmospheric composition while increasing global warming [65]. Along with air pollution, bushfires impact the water and soil quality, affecting animals and vegetation. Further, the remaining ash from bushfires gets washed away into water streams, resulting in water pollution affecting riverine biodiversity, and the remaining ash is a main source of environmental pollution [66]. There is an enormous effect of wildfires on ecology and terrestrial biodiversity, which can even result in the ultimate adverse effect of the extinction of species [67,68]. Detecting the effects of wildfires on animal species and plants is difficult. However, this is more often measured in terms of burned area, and the 2019–2020 Australian bushfire season burned more than 7 million hectares while affecting an estimated 3 billion animals [67]. Therefore, considering environmental and socio-economic aspects, bushfires pose a severe threat, and bushfire management remains challenging.

(a) (b) (c)

Figure 4. Bushfire consequences: (**a**) impact on the environment and ecology; (**b**) air pollution by smoke; and (**c**) destruction of property [37,41,69].

5. Bushfire Management

The changing temporal and spatial circumstances of bushfires create complexities in adopting bushfire management strategies [70]. Conducting a spatiotemporal analysis of the fire regime is essential to understand the changing bushfire patterns and to develop robust bushfire management strategies (e.g., [71]). Bushfire management plans facilitate predicting and controlling fire regimes while assisting short-term recovery. Long-term aspects of bushfire management focus on promoting the adaptation of societies while enhancing the preparedness for large-scale bushfire events [37]. Another crucial aspect of bushfire management is to make assets more resistant to fire events. In addition, assets can be relocated away from bushfire susceptible locations wherever possible. Building elements such as cladding and vulnerable timber roofs can be made resistant to fires by opting for nonflammable alternate materials [72]. Different stakeholders' involvement in policymaking and public awareness is another crucial aspect of bushfire management. For example, the leave-early policy in Australia is well defined for people who are in the fire path [73]. Public awareness about the best practices in the event of a fire is essential for better outcomes. Further, bushfire-susceptible communities should be made aware of their capacity to cope with fire when it arrives. Forest fire management information systems are widely employed around the world for effective bushfire management, minimising the potential consequences. For example, in Canada, there are four main national forest fire management information systems, namely the Canadian Forest Fire Danger Rating System, Spatial Fire Management System, Canada's National Forest Fire Management Information System and the Fire Monitoring, Mapping and Modeling system (Fire M3) [74]. These systems use remote sensing data, such as satellite data, along with physical data, to present daily information about fire weather, probability of fire occurrence and fire propagation. Bushfire management strategies explored in this study are categorised into four aspects such as bushfire prediction, detection, suppression and prevention. The following sections summarise the relevant studies falling into each of the aforementioned categories, highlighting the advantages and shortcomings/limitations of each technique.

5.1. Bushfire Prediction

There are different aspects related to bushfire prediction such as the prediction of bushfire risk, bushfire occurrence, bushfire spread and bushfire-related consequences. Bushfire risk is most often defined in terms of "fire danger", which is evaluated by integrating individual and combined effects of fire weather conditions, topography and fuel conditions such as fuel type and fuel moisture content. The quantification of fire danger is carried out by defining different indices, which are functions of air temperature, relative humidity, precipitation, wind speed, fuel type and fuel moisture content [75]. Different countries have defined their own fire danger indices considering the pertaining topography and other related factors. For example, the Angstrom index [76] is used in the Scandinavian countries, the Nesterov index is widely used in Russia [77], the Canadian Forest Fire Weather Index (FWI) [45], the United States National Fire Danger Rating System (NFDRS) [46], the McArthur Forest Fire Danger Index (FFDI) is used for open forests in Australia [42], and the McArthur Grassland Fire Danger Rating System is used for grassland areas in Australia [42,78]. These indices provide bushfire danger ratings representing the susceptibility of a particular region to an event of bushfire. The broader aspect of bushfire risk must consider both bushfire danger and fire vulnerability. Figure 5 illustrates a framework for the assessment of bushfire risk. Bushfire danger is associated with the probability of fire occurrence and spread, whereas fire vulnerability must account for the socio-economic and environmental consequences of bushfires.

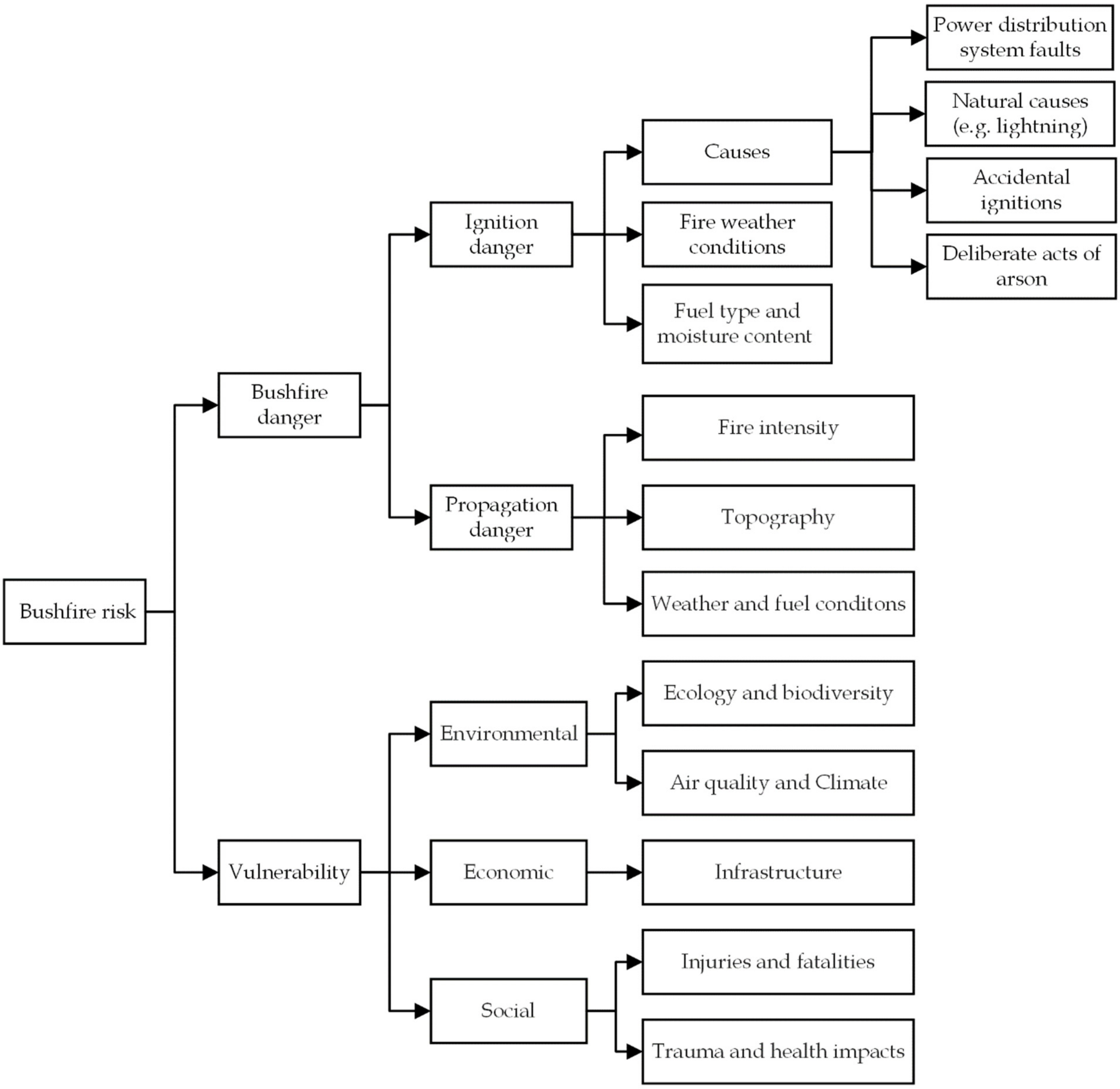

Figure 5. Framework for fire risk assessment.

Early attempts at the prediction of bushfire occurrence were by exploring the topographic conditions, meteorological variables, forest characteristics and fire statistics. The correlation between these factors and the probability of bushfire initiation was investigated. Zhang et al. [79] carried out a fire occurrence probability mapping of Northeast China by employing a binary logistic regression model. The spatial distribution of the fire occurrence probability was mapped by considering ten predictor variables, representing the topography, vegetation characteristics, meteorological variables and proximity to critical features such as water bodies. A multitemporal random sampling technique was employed to create the training subset, and bushfire data from 2000 to 2009 from Northeast China was used in developing the fire occurrence probability's spatial distribution model, and a 84.2% model fitness accuracy was obtained by assessing the area under the relative operating characteristic (ROC) curve. Further, it was found that the Normalised Difference Vegetation Index, which indicates the susceptibility of vegetation to fire, best explained the fire occurrence probability in the selected geographic region. A similar study was carried out by Catry et al. [11] to model the bushfire risk in Portugal. A 5-year period was considered to extract data, and 127,490 ignitions during this period were analysed. Logistic regression models were developed to estimate the likelihood of fire occurrence, and the results indicated that land cover, elevation and population density were crucial determinants of bushfire occurrence. Fuel characteristics such as fuel type, fuel load, moisture content and flammability heavily rely on the type of land cover, and it was found that 85% of the bushfires in mainland Portugal were located in agricultural and urban–rural interspersed areas. In addition, that study concluded that fire occurrence probability mapping can be further improved by incorporating more accurate and updated information. Information gained from remote sensing techniques like satellite imaging and other airborne sensing techniques facilitates improving bushfire management strategies by providing an opportunity to derive critical information. The following sections summarise the previous studies on bushfire prediction techniques incorporating remote sensing.

5.1.1. Satellite Imagery-Based Remote Sensing Techniques for Bushfire Prediction

Different remote sensing techniques have been widely employed in bushfire management. Early attempts for bushfire prediction consisted of aerial infrared scanners and radar-based techniques falling under the broad category of remote sensing (e.g., [80]). However, with the advancement of space explorations and satellite programmes, satellite imagery has emerged rapidly as a promising technique to aid bushfire prediction, considering the aspects of high spatial resolution, identification of fuel characteristics and bushfire susceptibility mapping [25]. Chuvieco and Congalton [81] explored the potential of producing bushfire hazard maps for the Mediterranean environment by incorporating data from Geographic Information Systems (GIS) and the digitally processed Thematic Mapper. The Thematic Mapper is an advanced multispectral scanning sensor introduced in the Landsat programme. This high-resolution imagery was capable of providing fine details about vegetation data while GIS processing created fire hazard models. To validate the bushfire hazard maps, an area that was already affected by bushfire was selected as the test area. The proposed integrated approach investigated different aspects such as fuel-oriented vegetation mapping, topographic data, proximity analysis and fire hazard modelling. Results indicated the enhanced bushfire mapping capability of the proposed method by applying remote sensing and GIS.

The identification of fuel characteristics such as fuel type, fuel load and moisture content is critical in determining bushfire danger and associated risk. Therefore, satellite imagery techniques are widely employed in developing fuel-type maps. However, the relatively coarse spatial resolution of data sources has limited the application of remotely sensed data for fuel mapping [82]. Typical remote sensed data used in this field are SPOT HRV (Systeme Pour l'Observation de la Terre-Haute Resolution Visible), Landsat MSS (multispectral scanner), Thematic Mapper or Enhanced Thematic Mapper, NOAA-AVHR and TERRA-AQUA MODIS. Arroyo et al. [82] presented a methodology for obtaining fuel maps using high-spatial-resolution satellite imagery by object-oriented classification. QuickBird imagery was used to classify the fuel type into one of six categories, and the selected study region was Madrid, Spain. The proposed methodology employing high-resolution imagery performed well compared with traditional pixel-based methods since the object-oriented approach allowed the context consideration. It was concluded that this technique had the potential to create accurate fuel maps with greater spatial resolution.

A similar study was carried out by Lasaponara and Lanorte [83] to characterise fuel type using very high resolution (VHR) QuickBird data. To evaluate the capability of the proposed method to classify fuel properties, an area with mixed vegetation cover and complex topography was analysed. The selected study area was in South Italy, with an extent of about 60 km^2. Actual field fuel-type classification was carried out before, after and during the acquisition of QuickBird data, and this was used as labelled data to assess the accuracy of the results of the test area. The main steps of the proposed method were the adaptation of Prometheus fuel types, the model construction and an accuracy assessment. Results indicated more than 75% accuracy for classifying fuel types using high-spatial- and -spectral-resolution remotely sensed data. Jaiswal et al. [25] explored bushfire risk zone mapping from satellite imagery and GIS. A bushfire-prone region in Madya Pradesh, India, was selected as the study region, and images from the Indian remote sensing satellite were used to produce vegetation maps. Topographic maps and field data were used in determining the slope and proximity to roads and settlements. Bushfire risk zones of the study area were identified by incorporating GIS and remote sensing satellite data. The likelihood of ignition and risk of fire spread was integrated into a bushfire risk.

There is a significant effect from the moisture content of fuel for bushfire initiation and fire propagation. Therefore, researchers have investigated different techniques to accurately estimate fuel moisture content. Chuvieco et al. [84] proposed an empirical approach to determine the fuel moisture content of Mediterranean grasslands and shrub species. Field measurements of moisture content were carried out for 6 years, out of which data from 4 years were used to derive the empirical relationship and the remaining data from 2 years were used to test the developed model. A multitemporal analysis was conducted for the NOAA-AVHRR data. The basis of the proposed methodology was a statistical fitting of the satellite remote sensing data and field-measured moisture content using a function representing the day of the year. The developed model was able to provide consistent fuel moisture content estimated with a coefficient of determination of more than 0.8 for both grasslands and shrub species. Other than the fuel moisture content, soil moisture and surface temperature also dictate the spread of bushfires. For example, lower surface temperatures and wet soils limit the spread of bushfires. Therefore, Chaparro et al. [85] explored the capability of predicting the extent of bushfires using remotely sensed soil moisture and surface temperature. The Iberian Peninsula in northwestern Spain was selected as the study area, and data extraction was carried out during the period from 2010 to 2014. Surface moisture and temperature conditions preceding a bushfire were analysed using SMOS-derived soil moisture data and surface temperature data. A regression model was developed between moisture-temperature conditions, land cover, region and month of fire outbreak as input variables and the maximum fire extent as the output. Model validation results showed around 83% accuracy, and the maximum error accounted for about 40.5 hectares. Thus, the developed model could predict the bushfire extent up to a reasonable accuracy by incorporating remotely sensed soil moisture–temperature trends.

Lozano et al. [86] modelled the bushfire occurrence probability by conducting a logistic regression analysis using multitemporal Landsat data. That study aimed to investigate the effect of prefire spectral indices on the prediction capability of fire occurrence. The Normalised Difference Moisture Index (NDMI), Normalised Difference Vegetation Index (NDVI), Normalised Burn Ratio (NBR) and the greenness of the Tasseled Cap transformation were considered as variables other than landscape variables when modelling the bushfire occurrence probability. It was found that the inclusion of spectral indices improved the fire prediction capability. These indices provided site-specific conditions while adding extra information other than the basic spatial patterns, ultimately contributing to the enhanced performance. It was concluded that a regression analysis incorporating satellite imagery and geographical information has the potential to better predict fire occurrence. The effect of satellite-based indices towards forecasting the fire danger in Boreal forests was explored by Akther and Hassan [87]. In that study, the Normalised Multiband Drought Index (NMDI), Temperature Vegetation Wetness Index (TVWI) and surface temperature for boreal forest regions of Alberta were determined from MODIS satellite data for the period from 2006 to 2008. The resulting predictions incorporating all three variables showed that 91.63% of the fires were categorised as very high, high and moderate fire danger classes. Therefore, the proposed technique had a good potential to forecast fire conditions by incorporating satellite-based indices and variables. A similar study was carried out by Chowdhury and Hassan [88] to develop a forest fire danger forecast system focusing on the Canadian province of Alberta. MODIS-derived data of the Normalised Multiband Drought Index (NMDI), NDVI and surface temperature were used as input variables in predicting the fire danger conditions. Considering the spatial and temporal dimensions, a gap-filling technique was implemented in that study to eliminate the gaps in input variables and to have a complete data set. The proposed methodology was implemented in estimating the fire danger in the 2011 fire season in Alberta, and the fire danger class "very high" resulted for most of the regions where actual severe fires occurred, illustrating the fire forecasting potential of the method.

Mallinis et al. [89] presented an integrated approach for fire management by combining local-scale fuel-type mapping with a fire behaviour simulation. High-resolution satellite imagery was used in performing fuel type mapping, and a site-specific fuel model was developed for the Mediterranean area. CART statistical modelling was employed to categorise the images into respective fuel types, and an overall accuracy of 80% was achieved. Once fuel sampling, image segmentation and classification were carried out, fire behaviour maps were generated using the FARSITE fire simulation model. Fire behaviour and growth were determined for different fuel models to facilitate bushfire management. In addition, fire line intensity and flame length maps were derived, which are of utmost importance for fire management authorities, illustrating the spatial scale of fire suppression. Bui et al. [90] mapped bushfire susceptibility for the Cat Ba National Park area in Vietnam. A GIS-based kernel logistic regression model was employed in predicting bushfire susceptibility. The first step of the study was data collection (historical fires and related factors) to develop the GIS database. Twenty-two historical bushfires in the selected study area, which occurred from 2009 to 2013, were extracted, and ten related factors determining the susceptibility to bushfires were investigated. Prefire spectral indices, landscape features and topography, weather conditions, proximity to settlements and roads were among the selected factors. The prediction capability of the trained kernel logistic regression model was evaluated using the ROC curve and five statistical evaluation parameters. Results indicated the capability of the proposed technique for bushfire susceptibility mapping to facilitate effective bushfire management practices.

With the advancement of computational power, there are vast developments in the field of machine learning, and these algorithms can be implemented for regression, classification and clustering [91]. Satellite imagery-based techniques for bushfire prediction integrate remote sensing data, GIS, topography and other related factors to predict bushfire risk, occurrence, propagation and consequences. Therefore, machine learning can effectively automate the prediction algorithms while improving the prediction capability. In addition, the generalisation and robustness of the algorithms can be improved when exposed to more data collected using satellite-based remote sensing. Researchers have effectively employed machine learning algorithms for feature extraction and model development for bushfire prediction. Maeda et al. [92] developed artificial neural network (ANN) models to forecast the spatial distribution of bushfire risk in the Brazilian Amazon using MODIS imagery. Similarly, Bisquert et al. [93] developed ANN and logistic regression models to obtain a fire danger model for the Galicia region of Northwest Spain using MODIS data. Lall and Mathibela [75] presented a novel data-driven system employing ANN models to predict the bushfire risk in the city of Cape Town in South Africa. In most of these studies, the output is a fire danger rating, which is a categorical variable such as "high risk", "moderate", and "low". Storer and Green [94] employed particle swarm optimisation instead of backpropagation to train ANN models to predict the bushfire size in Montesinho Natural Park in Portugal. Yu et al. [95] developed random forest models to predict bushfire risk using remotely sensed data for a study area in Cambodia. Bushfire risk ratings were derived using the trained models where the inputs were precipitation, land surface temperature, NDWI, NDVI, elevation, land cover and fire mask. Halgamuge et al. [96] explored the possibility of using deep learning techniques for predicting bushfire occurrences using actual weather data for a considered location. Six different optimisers, such as different gradient-based optimisation algorithms, were tested to identify the best optimiser to forecast the fire occurrence. Sharma et al. [23] investigated the use of remote sensing and meteorological data fusion in predicting bushfire severity for a study area in Australia. Four different tree-based ensemble machine learning models were employed, namely, random forest, fuzzy forest, extreme gradient boosting and boosted regressing tree. From the summary of the aforementioned studies, the potential of machine learning is evident for bushfire prediction.

5.1.2. Radars and Scanning-Based Techniques for Bushfire Prediction

The early conventional techniques to map the fuel types for bushfires were extensive fieldwork and aerial photography (e.g., [97]). However, as described in the previous section, satellite imagery-based remote sensing has evolved as a quick, reliable and efficient technique to use in bushfire prediction, given its high temporal and spatial resolution. Nevertheless, the difficulty in differentiating forest understory is a major limitation associated with interpreting satellite-based imagery. Light detection and ranging (LIDAR) techniques have the potential to address this issue. Airborne LIDAR techniques have demonstrated the capability to separate tree crowns from other canopy data, producing better results in predicting fire behaviour [98]. Riano et al. [80] used airborne LIDAR data to develop a model to automatically extract critical forest information to improve the fire behaviour models. A cluster analysis was employed to differentiate crown base height; thus, trees and understory canopy heights could be determined. Total tree laser hits and a total number of laser hits were used in determining the tree cover. Parameters such as tree height and cover, canopy height, surface canopy cover and crown bulk density were estimated from the proposed methodology, which could be used as inputs for fire models. It was concluded that LIDAR technology could enhance fuel characterisation capability to improve bushfire prediction accuracy. Mutlu et al. [99] presented a methodology to assess fuel models using LIDAR and multispectral remote sensing. The study area focused on was East Texas. In that study, several techniques, such as principal component analysis and minimum noise fraction, were explored for the data fusion of LIDAR and QuickBird imagery to assess fuel models. Further, the accuracy of fuel maps generated using LIDAR and QuickBird imagery were compared. Finally, accurate digital fuel maps were produced with a good spatial resolution. It was found that LIDAR-derived products accurately assessed fuel models, while the fusion of LIDAR data and QuickBird imagery increased the accuracy of classifying surface fuels.

The estimation of forest biomass and canopy fuel loads was carried out by Saatchi et al. [100] using radar remote sensing data. Multifrequency polarimetric synthetic aperture radar (SAR) imagery was used in that study to investigate the fuel load in Yellowstone National Park in the United States. Semiempirical algorithms were developed to predict the biomass, canopy fuel weight, canopy bulk density and foliage moisture content. These estimates were compared with field measurements to validate the proposed methodology, and a classification accuracy of more than 85% was obtained when different fuel load classes were considered. It was found that crown biomass and height were the most influential variables in estimating forest canopy fuel loads. It was concluded that high-resolution radar images integrated with weather data had great potential for predicting fire hazards. It is evident from these studies that radar and scanning-based techniques can be implemented effectively to address some shortcomings of satellite imagery-based remote sensing for bushfire prediction. A summary of the studies on bushfire prediction techniques is illustrated in Table 1. Previous studies covering the aspects of predicting bushfire risk, occurrence, spread and related consequences are summarised. Further, the studies on fuel type characterisation and fuel moisture content determination are included in Table 1.

Table 1. Summary of the studies on bushfire prediction techniques.

Study	Category	Content, Methods and Analysis Techniques
[79]	Mapping fire occurrence probability	Developed a fire occurrence probability spatial distribution model for Northeast China using binary logistic regression
[11]	Modelling and mapping bushfire risk	Estimated the likelihood of fire occurrence in Portugal via logistic regression models
[25]	Mapping bushfire risk zones	Identification of bushfire risk zones integrating GIS and remote sensing satellite data. Study region in Madya Pradesh, India
[81]	Mapping bushfire hazard	Produced bushfire hazard maps for the Mediterranean environment by incorporating data from GIS and digitally processed Thematic Mapper
[82]	Mapping fuel types	Developed fuel maps for Madrid, Spain, using high-spatial-resolution QuickBird satellite imagery by employing object-oriented classification
[83]	Characterising fuel types	Classified fuel types for a study area in South Italy using high-spatial- and -spectral-resolution satellite imagery
[84]	Determining fuel moisture content	Developed an empirical methodology to determine fuel moisture content by employing statistical fitting of the satellite remote sensing data and field-measured moisture content for Mediterranean grasslands and shrub species
[85]	Predicting bushfire extent	Developed a regression model to predict the extent of bushfires using remotely sensed soil moisture and surface temperature. Study area in the Iberian Peninsula in northwestern Spain
[86]	Modelling bushfire occurrence probability	Investigated the effect of prefire spectral indices on the prediction capability of fire occurrence by conducting a logistic regression analysis using multitemporal Landsat data
[87]	Assessing bushfire danger conditions	Assessed the effect of satellite-based indices in forecasting the fire danger in Boreal Forest regions of Alberta, Canada
[88]	Predicting bushfire danger conditions	Developed a forest fire danger forecast system for Alberta, Canada, using MODIS-derived data. A gap-filling technique was implemented in this study to eliminate the gaps in input variables
[89]	Fuel-type mapping and fire behaviour simulation	High-resolution satellite imagery was used in performing fuel-type mapping, and a site-specific fuel model was developed for the Mediterranean area. CART statistical modelling was employed to categorise the images
[90]	Mapping bushfire susceptibility	A GIS-based kernel logistic regression model was developed to predict bushfire susceptibility of the Cat Ba National Park area in Vietnam
[92]	Forecasting bushfire spatial distribution	Developed ANN models to forecast the spatial distribution of bushfire risk in the Brazilian Amazon using MODIS imagery
[93]	Modelling bushfire danger	Developed ANN and logistic regression models to obtain a fire danger model for the Galicia region of Northwest Spain using MODIS data
[94]	Predicting bushfire size	Trained ANN models by employing particle swarm optimisation instead of backpropagation to predict the bushfire size in Montesinho Natural Park in Portugal
[95]	Predicting bushfire risk	Developed random forest models to predict the bushfire risk using remotely sensed data for a study area in Cambodia

Table 1. *Cont.*

Study	Category	Content, Methods and Analysis Techniques
[96]	Predicting bushfire occurrences	Explored the possibility of using deep learning techniques for predicting bushfire occurrences using actual weather data for a considered location
[23]	Predicting bushfire severity	Investigated the use of remote sensing and meteorological data fusion in predicting bushfire severity for a study area in Australia. Random forest, fuzzy forest, extreme gradient boosting and boosted regressing tree machine learning models were employed.
[80]	Improving fire behaviour models	Developed a model using airborne LIDAR data to automatically extract critical forest information to improve the fire behaviour models. A cluster analysis was employed to differentiate crown base height and to determine trees and understory canopy heights
[99]	Generating and assessing fuel maps	Assessed fuel models using LIDAR and multispectral remote sensing. Principal component analysis and minimum noise fraction techniques were explored for the data fusion of LIDAR and QuickBird imagery
[100]	Estimating forest biomass and canopy fuel loads	Developed semi-empirical algorithms to predict forest biomass and canopy fuel loads using SAR remote sensing data. Study region in Yellowstone National Park in the United States

5.2. Bushfire Detection

There are different techniques implemented for bushfire detection and monitoring. Over the years, significant efforts have been put into developing advanced and reliable early bushfire detection methods to supplement efficient bushfire management systems. Early attempts at bushfire detection were made by human observers on watch towers. However, the subjectivity of human observations has hindered the reliability of detection. Furthermore, relying solely on human observers for monitoring vast forested areas is unfeasible, and the challenging working conditions for human observers have spurred the development of alternative surveillance methods. Modern bushfire detection techniques can be categorised as terrestrial systems and aerial systems [101].

Terrestrial systems are based on wireless sensor networks, camera surveillance and video surveillance (e.g., [102–104]). Camera surveillance and video surveillance can provide automatic bushfire detection, replacing conventional human observation. These techniques are often integrated with advanced image processing methods and computer vision to enhance the accuracy of bushfire detection. Surveillance instruments like cameras, video monitoring devices and sensor devices can be placed in watch towers, and the output data from these systems are linked with alarm systems to notify relevant authorities. In addition to traditional low-resolution cameras, thermal and infrared cameras can also be utilised for bushfire detection, particularly for nighttime and low-light surveillance situations [21]. Key advantages of camera surveillance are the wider coverage area from multiple cameras, which can be operated from a single monitoring spot and zooming capability to have fine observations in a suspected area. Further, video surveillance can be extremely useful in postfire analysis [101]. Wireless sensor networks are used to monitor field conditions such as the surface temperature, relative humidity and wind speed, along with GPS locations. Sensor data are transmitted to a base station, which then transfers the gathered data to software running on a database server for the purpose of concluding the decision-making process [104]. Nonetheless, installing sensors across wide forests may not be economically viable. This is the main drawback of wireless sensor-based bushfire detection techniques, and up to date, there is only a limited percentage of forests covered by cameras and sensors [101].

Aerial systems for bushfire detection consist of observations from manned and unmanned aerial vehicles and satellites. Aerial vehicles can efficiently manoeuvre into impacted areas for fire monitoring, and they are often equipped with sensors such as LIDAR and infrared to assess field conditions. Considering the financial benefits and simplicity of operation, unmanned aerial vehicles (UAVs) have become a feasible alternative to address the issues in bushfire detection [21]. In addition, aerial systems can provide imagery of difficult-to-reach locations, providing safer operation conditions. Unlike terrestrially deployed systems, satellite imagery can cover large areas [32]. However, the operational cost of satellites and the required technical competence is high compared to other techniques. In addition, some satellite imagery's temporal and spatial resolution is low, which can negatively affect the detection accuracy.

5.2.1. Satellite Imagery and Sensor Data-Based Bushfire Detection

Satellite imagery effectively tracks ongoing wildfires across extensive spatial and temporal ranges [26]. These monitoring systems require frequent and well-characterized information to perform analysis and make decisions. Satellites can be broadly categorised as geostationary and non-geostationary. Non-geostationary satellites offer a larger spatial coverage along with the drawback of longer refresh intervals. Non-geostationary satellites include NASA's earth observing TERRA and AQUA satellites and Landsat satellites jointly managed by NASA and the US Geological Survey [105]. MTSAT (Multifunctional Transport Satellite), GOES (Geostationary Operational Environmental Satellites), COMS (Communication, Ocean and Meteorological Satellite) and MSG (Meteosat Second Generation) are some examples of geostationary satellites employed for bushfire detection [106–110]. These satellites are well equipped with sensors and other instruments to facilitate imagery. Some of these instruments are Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High Resolution Radiometer (AVHRR), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Enhanced Thematic Mapper (ETM) [111–113]. Even though polar orbiting satellites can provide excellent imagery that can cover wide areas, the temporal resolution of this information may not be sufficient to monitor active fires. For example, the temporal resolution of non-geostationary satellite data MODIS is six hours in Australia [26]. Further, detecting small bushfires, nocturnal fire detection, the elimination of cloud effects and the extraction of bushfire features from satellite imagery have been challenging. Therefore, significant effort has been put into developing active fire products, advanced image processing, machine learning and automated fire detection techniques based on satellite imagery.

Remotely sensed fire data sets produced by MODIS are known as MODIS active fire products, and these fire products undergo periodic reprocessing to incorporate algorithm modifications and refinements. Giglio et al. [114] presented improvements made to the MODIS fire detection algorithms. The main intention of that work was to address the issues related to the previous version of the fire product. Some of these issues were the occurrence of false alarms, often triggered by minor forest clearings, and the possibility of overlooking significant fires concealed by thick smoke. In addition, a radiance-based approach was utilised to retrieve the fire radiative power (FRP), resulting in only a marginal reduction in FRP for high-intensity fire pixels while having a significant reduction for all other events. The proposed advancements were confirmed through validation using reference fire maps generated from over 2500 ASTER images.

Fire products from satellites can be categorised into two groups. One is referred to as active fire detection, where binary fire maps ("yes/no") are derived using flagging pixels. The other group is where satellite pixels are partitioned into smouldering, flaming and unburned areas by assigning temperature values [115]. Csiszar et al. [115] investigated the validation of MODIS active fire products in Siberia. Spatial patterns of flaming were characterised at the pixel level using ASTER imagery. This study highlighted the issues related to active fire validation. It was found that the MODIS algorithm existing at that time had lower-than-expected detection rates for Siberia, mainly due to the overseen flames under heavy smoke. A cluster-based analysis was proposed in that study to address the issues related to heavy smoke. The detection of smaller fire events using MODIS fire products and the minimisation of bushfire false alarm rates are two key areas that have been investigated. Giglio et al. [111] presented an enhanced contextual fire detection algorithm for MODIS. This improved algorithm was found to be more sensitive to smaller, cooler fires while significantly reducing false alarms. A performance evaluation of the proposed method was carried out using a theoretical simulation and ASTER imagery. Results indicated that the improved algorithm reduced the false alarm rates 10–100 times while detecting bushfires approximately half the minimum size of those detected from the original algorithm.

Lightning is a major natural cause of the initiation of bushfires. Analysing the lightning patterns in a specific area can aid in comprehending the occurrences of bushfires ignited by lightning strikes. Bar-Massada et al. [105] combined satellite-based fire observations (MODIS data) and ground-based lightning detections to detect lightning-caused bushfires in the USA. Data from the National Lightning Detection Network were employed to identify lightning strikes, and the developed algorithm searched for the correlation between these strikes and MODIS fire clusters. Results showed the capability of the proposed method in detecting broad-scale spatiotemporal patterns of lightning-initiated bushfires in the US. Nevertheless, it should be noted that the detection of smaller bushfires was constrained, which is an inherent limitation associated with MODIS data. Similar to MODIS data acquired from the TERRA and AQUA earth-orbiting satellites, Landsat operational land imager data can be effectively employed in active fire detection.

Schroeder et al. [32] presented an active fire detection algorithm based on Landsat operational land imager data. This algorithm utilised fire-sensitive infrared shortwave channels and incorporated a multitemporal analysis to enhance pixel classification outcomes. Through initial visual image analysis, it was observed that the algorithm demonstrated a high accuracy and consistency across various scenarios involving biomass burning and gas flares. Further, field-data verification corroborated the algorithm's capability to detect fires in considerably smaller areas when compared to existing operational satellite fire products. The introduction of multitemporal analysis tests applied to pixels located in the same vicinity resulted in a substantial reduction in commission errors, with a global average of less than 0.2%. Thus, active fire detection algorithms utilising Landsat data hold significant potential.

The use of National Oceanic and Atmospheric Administration (NOAA) AVHRR data for fire detection was explored by Flasse and Ceccato [116]. In that study, a contextual algorithm was developed for AVHRR data-based fire detection. In visual image interpretation, the human eye often identifies a fire because of the noticeable contrast in temperature between the fire itself and its environment. The contextual algorithm functioned in a comparable way, making a determination about whether a pixel corresponded to a fire by examining its characteristics in comparison to those of its neighbouring pixels. Initial results indicated the applicability of the proposed technique for automatic fire detection. Nonetheless, commission errors did occur as a result of clouds and cooler backgrounds that were not uniformly distributed around a hot area. Schroeder et al. [117] introduced a Visible Infrared Imaging Radiometer Suite (VIIRS) sensor data-based active fire detection algorithm. That algorithm utilised thermal infrared imagery data to identify daytime and nighttime burnings as well as other thermal anomalies. The proposed algorithm was constructed based on the well-established MODIS fire product, which was developed, validated and refined over the course of several years. VIIRS fire data exhibited notably improved mapping capabilities in comparison to the existing MODIS fire detection data. In addition, the outcomes revealed the enhanced consistency of the proposed algorithm in differentiating the bushfire perimeter.

Nocturnal fire detection is another crucial aspect of a bushfire management system. Polivka et al. [118] explored the use of VIIRS data to develop a fire detection algorithm that detected gas flares and biomass burning at night. That technique characterised fire pixels integrating both infrared signatures and visible light. The validation of the proposed technique was carried out using fine-resolution ASTER data. The reported findings suggested that, in contrast to the traditional VIIRS fire algorithm employed during the study period, the proposed technique, which incorporated adjustments to enhance the detection of low-temperature hotspots, exhibited a significant increase in the number of identified fire pixels.

Information gathered from geostationary satellites can also be analysed and utilised to develop techniques for detecting and tracking bushfires. Xu and Zhong [26] investigated the utilisation of infrared imagery acquired from the Himawari-8 geostationary satellite for the development of a real-time bushfire detection algorithm. In Australia, that satellite provides infrared imagery at a spatial resolution of 2 km at intervals of 10 min. The foundation for creating that algorithm stemmed from the MODIS fire product, and multispectral imagery from Himawari-8 was employed to identify hotspots, with updates available every 10 min. The performance of the developed algorithm was evaluated by analysing a case study of the 2015 Western Australia bushfires. The results demonstrated that that technique was sensitive to small bushfires and remained robust in the presence of smoke and thin clouds. A similar study was conducted by Xu et al. [119], employing imagery from Geostationary Operational Environmental Satellites (GOES) to detect active fires and assess the FRP. That approach used near-real-time FRP products from Spinning Enhanced Visible and Infra-Red Imager (SEVIRI) and developed an algorithm considering the study regions of North, South and Central America. Outputs of the algorithm from GOES imagery were compared with well-established MODIS fire products. The identification of clouds and fires from GOES imagery closely aligned with the MODIS fire product when the omission error was less than 10%. Advanced geostationary sensors have the capability to supply supplementary data that describe the background temperature. Hally et al. [120] proposed a multitemporal technique for diurnal temperature fitting from Himawari imagery in that context. The fitting of the idealised background temperature served as a reference for setting thresholds on the sensor’s brightness temperature data. That approach was employed to establish a method for determining both the timing and likelihood of thermal anomalies. The outcomes revealed that the suggested approach could detect between 75 and 99% of thermal anomalies that were identified by low-Earth-orbiting satellites during the study duration.

Analysing satellite imagery for active fire detection is a complex process given the aspects of small fire detection, nocturnal fire detection, disturbance from clouds and difficulty in identifying fires concealed by smoke. Therefore, the possibility of incorporating machine learning and deep learning algorithms for fire detection and classification from satellite imagery has been explored by researchers. Priya and Vani [121] investigated the use of convolution neural network-based transfer learning to classify satellite imagery into fire and nonfire classes. That technique could overcome the manual selection of input features from satellite imagery and hand-crafted algorithms for classification, which are commonly used in conventional algorithms. Experimental results illustrated the proposed method’s higher classification accuracy, which incorporated automatic feature extraction. A similar study was conducted by Kumar et al. [122], where K-nearest neighbour and artificial neural network (ANN) algorithms were explored to classify active bushfires in Australia. Training and testing were carried out using actual data extracted from satellite imagery. Reasonable classification accuracies were obtained for both techniques, and the trained ANN model had better accuracy than the K-nearest neighbour algorithm. Phan et al. [123] developed a multiscale deep neural network model to detect and locate bushfires from satellite imagery integrated with weather data. The research demonstrated that a precise spatiotemporal alignment of weather information could significantly enhance the classification accuracy of the proposed deep learning technique based on satellite imagery. When evaluating the performance of the proposed algorithm using real-world data, an overall classification accuracy of 93.4% was achieved. The potential of machine learning approaches for active bushfire detection is evident from these studies. A summary of the studies on satellite imagery-based bushfire detection techniques is illustrated in Table 2.

Table 2. Summary of the studies on satellite imagery-based bushfire detection techniques.

Study	Satellite, Sensors and Data	Content, Analysis Techniques and Remarks
[114]	TERRA and AQUA satellites, MODIS	Proposed improvements to the MODIS fire detection algorithms by integrating a radiance-based approach
[115]	MODIS, ASTER	Investigated the validation of MODIS active fire products in Siberia. Spatial patterns of flaming were characterised at the pixel level using ASTER imagery, and a cluster-based analysis was proposed.
[111]	MODIS, ASTER	Presented an enhanced a contextual fire detection algorithm for MODIS, and the improved algorithm was found to be more sensitive to smaller, cooler fires while significantly reducing false alarms
[105]	MODIS, ground-based lightning detections	Detected lightning-caused bushfires in the USA by combining satellite-based fire observations (MODIS data) and ground-based lightning detections
[32]	Landsat, operational land imager	Developed an active fire detection algorithm based on Landsat operational land imager data. The introduction of multitemporal analysis tests resulted in a substantial reduction in commission errors.
[116]	NOAA-AVHRR	Developed a contextual algorithm for AVHRR data-based automatic fire detection. Commission errors were present because of clouds and cooler backgrounds that were not uniformly distributed around a hot area.
[117]	VIIRS, MODIS fire product	Developed an active fire detection algorithm utilising thermal infrared imagery data to identify daytime and nighttime burnings as well as other thermal anomalies
[118]	VIIRS, ASTER	Explored the use of VIIRS data to develop a fire detection algorithm that detects gas flares and biomass burning at night
[26]	Himawari-8 geostationary satellite, infrared imagery	Investigated the utilisation of infrared imagery acquired from the Himawari-8 satellite for the development of a real-time bushfire detection algorithm. The developed technique was sensitive to small bushfires and remained robust in the presence of smoke and thin clouds.
[119]	GOES, SEVIRI	Employed GOES imagery to detect active fires and assess fire radiative power for the study region of North, South and Central America
[120]	Himawari satellite	Proposed a multitemporal technique for diurnal temperature fitting from Himawari imagery. Established a method for determining both the timing and likelihood of thermal anomalies.
[121]	TERRA and AQUA satellites, MODIS	Investigated the use of convolution neural network-based transfer learning to classify satellite imagery into fire and nonfire classes
[122]	LANCE FIRMS	Explored K-nearest neighbour and artificial neural network (ANN) algorithms to classify active bushfires in Australia
[123]	GOES, weather data	Developed a multiscale deep neural network model to detect and locate bushfires from satellite imagery integrated with weather data

5.2.2. Wireless Sensor Network Data-Based Bushfire Detection

Bushfires are associated with pertaining environmental and weather conditions. Therefore, measurement data about these conditions can assist bushfire detection and monitoring systems. With the advancement of sensor technology, more powerful sensors offer additional benefits such as smaller size, lower cost and increased power efficiency [21]. Wireless sensor networks can be employed to measure field conditions such as surface temperature, relative humidity, light condition, wind speed and smoke density, which are directly related to bushfire initiation and propagation. Various types of sensors, such as thermal, LIDAR, infrared and vision sensors, can be deployed to acquire field measurements. The description of attributes for each sensor type is not presented here, and it can be found in the works of Partheepan et al. [21]. Measurements of sensor networks can be integrated with topography, vegetation patterns and fuel characteristics in a particular area to estimate bushfire risk, while sensor data alone can detect and monitor bushfires.

Chen et al. [124] designed a fire detection system based on multisensor data fusion. Surrounding temperature, smoke density and carbon monoxide (CO) density were recognised as the primary parameters for fire detection, as they represent key characteristics inherently associated with fires. Data-fitting characteristics and fire-experience characteristics were extracted and fused via a fuzzy inference system to obtain the final fire probability. The experimental testing yielded satisfactory results for various fire types. Data fusion has the potential to enhance detection precision while mitigating the impact of disturbances. Hefeeda and Bagheri [125] designed a wireless sensor network for early bushfire detection. The problem of forest fire detection was formulated as a node k-coverage problem within wireless sensor networks. The sensor network was designed based on the fine fuel moisture code and the Fire Weather Index, which are the key components of the FWI system. Simulation results demonstrated the proposed technique's enhanced performance considering detection accuracy, faster convergence and extended network lifetime. A similar study was carried out by Zervas et al. [126], which proposed a fire detection methodology based on multisensor data fusion. Two types of sensors were employed in that sensor network such as infield and outfield sensors. In the urban–rural interface area, infield sensors were distributed to collect temperature and humidity measurements, whereas outfield sensors consisted of vision sensors that monitored the same geographical region. Information from nearby sensor nodes was analysed by comparing it to identify changes in the underlying data distribution, serving the purpose of identifying potential fires and generating fire alarms.

Díaz-Ramírez et al. [127] developed bushfire detection algorithms that relied on information fusion techniques, leveraging data collected from wireless sensor networks. One of the devised algorithms utilised a threshold-based approach, and the sensor nodes were equipped with light, humidity and temperature sensors. The Dempster–Shafer theory was employed in another algorithm, assuming that the nodes utilised temperature and humidity sensors. Results demonstrated both algorithms could detect fires in the initial stage. Nevertheless, false positives were observed when motes were exposed to direct sunlight. To mitigate this issue, it was necessary to provide cover for the motes to prevent direct sunlight exposure. Doolin and Sitar [104] designed a bushfire detection system integrating wireless sensor data and field-testing results. Environmental sensors recorded relative humidity, temperature and barometric pressure along with GPS locations. A performance evaluation of the proposed technique was conducted via two prescribed burns in California. Sensors within the burn area detected the flame front before it could escalate into a widespread fire. The sensors recorded a rise in temperature along with a decrease in barometric pressure and humidity as the flames approached. Results demonstrated the potential of the developed technique for commercial development.

The interpretation of large quantities of sensor data in a wireless sensor network can be complex. Therefore, machine learning algorithms have been integrated into sensor data analysis to automate bushfire detection algorithms. Arrue et al. [128] developed a bushfire detection algorithm that reduced false alarm rates. That algorithm incorporated visual infrared image matching, meteorological and geographic data, memory of past events and image processing techniques. ANN models were utilised to conduct the analysis, aiming to derive a probability score indicating the likelihood of a bushfire triggering an alarm. In a similar study conducted by Yu et al. [129], ANN models were employed to process the data gathered from wireless sensor networks for bushfire detection. Relative humidity, wind speed, smoke and temperature data were collected from field sensors. The developed ANN model operated on a large volume of raw data, effectively extracting valuable information for decision-making, while minimising communication overhead and conserving energy. Nosouhi et al. [30] developed a machine learning-based approach to detect bushfires using sensor measurements of environmental parameters. The machine learning model was trained using one year of field sensor data, demonstrating the typical spatiotemporal patterns in environmental data. When there were deviations from the normal, these anomalies were recognised as having the potential to trigger a bushfire. Experimental results demonstrated the effectiveness of the proposed method in detecting early bushfire symptoms. These studies demonstrate the capability of wireless sensor networks for bushfire detection. The summary of the studies employing wireless sensor networks for bushfire detection is illustrated in Table 3.

Table 3. Summary of the studies on wireless sensor network-based bushfire detection techniques.

Study	Sensors Collected Data	Content, Analysis Techniques and Remarks
[124]	Surrounding temperature, smoke density and carbon monoxide (CO) density	Designed a fire detection system based on multisensor data fusion. Data-fitting characteristics and fire-experience characteristics were extracted and fused via the fuzzy inference system to obtain the final fire probability.
[125]	Fine fuel moisture code and Fire Weather Index	Formulated the bushfire detection problem as a node k-coverage problem within wireless sensor networks.
[126]	Infield sensors (collected temperature and humidity measurements), outfield sensors (vision sensors)	Proposed a fire detection methodology based on multisensor data fusion. Information from nearby sensor nodes was analysed by comparing it to identify changes in the underlying data distribution to identify fires and generate fire alarms.
[127]	Light, humidity and temperature sensors	Developed bushfire detection algorithms that relied on information fusion techniques, leveraging data collected from wireless sensor networks. Adopted Dempster–Shafer theory and threshold-based approaches.
[104]	Environmental sensors (recorded relative humidity, temperature and barometric pressure), GPS locations	Designed a bushfire detection system integrating wireless sensor data and field-testing results to detect flame front before it could escalate into a widespread fire
[128]	Visual infrared images, meteorological and geographic data	Developed a bushfire detection algorithm that reduced false alarm rates by employing ANN models to perform the analysis, aiming to derive a probability score indicating the likelihood of a bushfire triggering an alarm
[129]	Field sensors (collected relative humidity, wind speed, smoke and temperature data)	Employed ANN models to process the data gathered from wireless sensor networks for bushfire detection. The developed model operated on a large volume of raw data, effectively extracting valuable information for decision-making.
[30]	Temperature and humidity data	Developed a machine learning-based approach to detect bushfires using sensor measurements of environmental parameters. Utilised classification and regression trees (CARTs), random forest (RF) and support vectormachine algorithms.

5.2.3. Application of Unmanned Aerial Vehicles (UAV) for Bushfire Detection

Unmanned aerial vehicles (UAVs), more commonly known as drones, can be employed for data collection while patrolling over forests, with the primary goal of detecting and monitoring bushfires. The primary benefits of UAV-based fire detection systems include enhanced personal safety, extended operational coverage and swift manoeuvrability. UAV-based data collection is carried out via different types of sensors such as visual cameras, infrared cameras, thermal cameras, optical flow sensors, gas sensors, humidity sensors and GPS [21,130]. Another critical component of a UAV-based fire monitoring and detection system is the guidance, navigation and control system for both single and multiple UAVs. When a fleet of UAVs is deployed, control systems should be capable of finding optimum paths to cover the fire areas. Furthermore, it is essential to establish a ground station to support communication, perform ground-based computations and trigger automatic fire warning alarms. The predominant challenge associated with UAV imagery is the impact of vibrations and motion, which can lead to image blurring [131]. Consequently, ongoing efforts encompass software and hardware development to mitigate this issue. UAV-based fire detection systems are extensively used in conjunction with computer vision for image processing. This is done to extract fire-related features, enabling informed decision-making and the generation of fire warning alarms in automated detection systems. Machine learning algorithms are also incorporated with UAV-based fire detection systems to collect the information from sensors and automate the decision-making process while enhancing detection accuracy (e.g., [132,133]). Table 4 provides an overview of past research regarding the use of UAVs in the field of bushfire detection and monitoring. The outcomes of previous research demonstrate the potential of UAVs, when equipped with suitable sensors, to detect bushfires early and activate warning alarms.

Table 4. Applications of UAVs for bushfire detection.

Study	Sensors	Content, Analysis Techniques, Remarks
[134]	Visual camera	Developed a bushfire detection and monitoring technique by leveraging visual sensors mounted on UAVs. This approach capitalised on both colour and motion features to augment the algorithm's performance and reduce false alarms.
[135]	Optical flow sensors	Developed a bilateral aerial teleoperation system for detecting and monitoring bushfires. Velocity synchronisation was proposed to achieve motion tracking of the master and slave UAVs, while a modified wave variable method was employed to address time-varying delays.
[136]	Visual and infrared cameras	Proposed an automatic fire detection methodology integrating the information from a fleet of UAVs. The improved endurance of UAVs and their enhanced resilience to smoke effects bolstered the detection capabilities of that technique
[137]	Smoke detector, microwave radiometer and gas sensors	Developed an early bushfire detection system employing UAVs equipped with smoke detectors, gas sensors and thermal cameras to detect hotspots
[138]	Infrared camera	Introduced an efficient UAV path-planning algorithm that leveraged real-time infrared image data collected onboard multiple small UAVs for the purpose of monitoring forest fires. Challenges of refuelling and accommodating irregular and growing fire shapes need to be addressed.
[139]	Visual and infrared cameras	Developed a perception system for bushfire monitoring which involved a fleet of UAVs. That system integrated information to estimate the real-time evolution of bushfires.
[140]	Surveillance camera	Introduced a block-based bushfire detection method using deep neural network models, which utilised transfer learning to enhance the detection rates
[132]	Humidity sensor, barometer, global positioning sensor and compass	Developed an automated early-warning system for bushfires by harnessing multiple sensor data collected from UAVs and employing deep learning and YOLO algorithms
[133]	Visible or infrared camera	Developed a deep learning-based bushfire detection approach using UAV imagery. Leveraging the existing computational resources onboard, a convolutional neural network was implemented using YOLOv3.
[141]	Infrared camera, GPS	Developed a video-based fire detection system by utilising deep learning approaches. The developed model demonstrated a high average precision and fast inference speed, enabling real-time fire detection.

Despite the promise exhibited by UAV-based fire detection and monitoring systems, technical challenges must be tackled to enhance the capabilities of UAVs in this domain. The energy limitation of UAVs stands out as a primary concern that demands resolution. UAVs rely on onboard batteries to power all their operations, and the payload capacity limitations of UAVs make it impractical to carry large batteries [142]. Therefore, UAV operations cannot be continued for extended periods. Furthermore, there are constraints associated with lightweight cameras, particularly concerning their radiometric and geometrical properties [21]. There are special requirements for cameras used for remote sensing compared to general-purpose cameras. The inaccuracy of GPS signals during UAV operations is identified as another challenging issue, particularly for path planning. Relying solely on onboard sensors may not suffice for accurate localisation. Moreover, the collaboration of multiple UAVs to minimise synchronisation issues and optimise path planning is crucial. These aspects warrant further investigation to enhance the accuracy of bushfire detection through UAV-based techniques.

5.3. Bushfire Suppression and Prevention

Bushfire suppression, often referred to as firefighting, is carried out to minimise the extent of the burned area by containing the fire within a limited region before it has the chance to escalate into a widespread blaze. The effectiveness of suppression efforts is typically assessed based on two key metrics: the time taken to achieve containment and the ultimate extent of the burned area. A wide array of factors can influence bushfire suppression efforts, including factors such as prevailing weather conditions, the type of vegetation in the area, the topography of the terrain and the speed of the response to the fire. The probability of containing a bushfire reduces with the increase in the severity of fire weather conditions, which are generally measured by the Forest Fire Danger Index [143]. Additionally, the kind of vegetation strongly influences the associated fuel type, resulting in varying fire behaviours across different vegetation types [144]. The fuel loads, which impact spread rates, spot-fire generation, flame dimensions and accessibility, show a strong correlation with the likelihood of successfully containing forest fires [145].

The most common approaches employed for bushfire suppression include deploying ground firefighters and utilising aerial bushfire suppression methods [146,147]. The chemicals used in firefighting efforts may encompass a range of substances, including water, water enhancers like foams and gels, as well as specially designed fire retardants [148]. In aerial suppression, firefighting aircraft play a crucial role in enhancing the effectiveness and efficiency of ground suppression forces. Aerial drops are frequently employed to combat flames and decelerate the advance of fires ahead of ground resources. This approach makes the process of extinguishing flames safer and facilitates the overall firefighting efforts. Plucinski et al. [146] compared bushfires' containment time with and without aerial suppression's support. An analysis of 251 bushfire incidents, incorporating input from senior firefighting personnel, led to the conclusion that aerial suppression is the most effective method for reducing fire containment time in challenging wildfire suppression scenarios. These challenges can be high fuel hazard ratings, adverse weather conditions, steep slopes, extended resource response times and large burning areas at the initial attack.

The time taken for the initial attack, which refers to the first response of firefighting assets in fire suppression, plays a pivotal role in the success of bushfire suppression efforts. When there is a delay in the initial attack, the fire head can become excessively intense, the perimeter can expand significantly, and the fire's growth rate may be too rapid for immediate containment when fire crews arrive at the scene [37,149]. Plucinski [145] identified the most influential predictor variables for defining the success of an initial attack based on both time and area, using a dataset that focused on Australian wildfires occurring in areas dominated by forests and shrubs and involving aerial suppression. That analysis of 334 Australian bushfires determined that the likelihood of widespread bushfires was associated with factors such as the fire area at the time of the initial attack, the level of fuel hazard, and the Forest Fire Danger Index. Furthermore, there was a strong correlation between the fire area at the time of the initial attack and the delay in aerial suppression efforts. Podur and Martell [34] developed a simulation model for the growth and suppression of bushfires in Ontario, Canada. A logistic regression model was constructed using weather and suppression data to forecast the probability that a bushfire would escape the initial attack and expand to cover an area exceeding 100 hectares. This research revealed that severe weather conditions can limit the effectiveness of fire suppression efforts, even though bushfire suppression itself has a significant impact on reducing the extent of fire burn areas. In addition to these studies, the economic aspect of bushfire suppression has been comprehensively investigated by researchers to optimise the cost while enhancing the benefits of fire suppression (e.g., [35,150,151]).

Preventive measures to minimise the adverse effects of bushfires include relocating assets to fire-free or less exposed places, increasing the robustness of infrastructure to resist fires and managing flames responsibly. In addition, bushfires initiated due to the failure of the power distribution infrastructure can be minimised by employing accurate and reliable condition assessment techniques to detect their defects at an early stage [50,54,55,152]. Failure preventive maintenance should be carried out to have safe power distribution infrastructure. Further, community awareness regarding bushfire response and knowing the immediate actions to take in the event of a bushfire is of utmost importance in minimising the destruction caused by bushfires [153]. In addition to implementing preventive measures against bushfires, developing strategies that focus on enhancing recovery efforts following a bushfire event is essential.

6. Summary and Discussion

This paper provides a comprehensive discussion of various facets related to bushfires, encompassing topics such as bushfire initiation, fire weather conditions, the detrimental impacts of bushfires and strategies for bushfire management. Bushfires can originate from a multitude of sources, including power distribution system malfunctions, unintentional ignitions, natural phenomena and deliberate acts of arson. While certain causes like lightning strikes are beyond our control, others are susceptible to mitigation or even total prevention. If severe fire weather conditions persist, the influence of these factors in triggering a spark is greatly intensified. These adverse fire weather conditions typically involve increased wind speeds, elevated air temperatures and decreased relative humidity. Moreover, the amount of rainfall that precedes a bushfire plays a crucial role in determining the moisture levels in both the soil and the fuel, which are pivotal factors influencing the initiation and spread of bushfires. Additionally, the topography and vegetation patterns in a specific area dictate fuel characteristics that can contribute to fire initiation. A thorough comprehension of the factors contributing to bushfire initiation, encompassing weather conditions, topographical features and fuel characteristics, can enable a precise assessment of fire danger within a specific region.

Among the various adverse impacts of bushfires, the loss of lives stands as a prominent and tragic outcome. In addition to fatalities, injuries and the trauma experienced by bushfire-prone communities, health issues arising from exposure to smoke containing harmful gases emerge as significant social aspects of bushfires. The adverse economic consequences of bushfires encompass a range of factors, including infrastructure damage, disruptions to farming, tourism and other industries, expenses related to injuries resulting from fires, the cost of implementing fire safety measures and the financial burden of fire service response efforts. In addition to social and economic consequences, bushfires also have substantial environmental implications. Some of the primary environmental concerns associated with bushfires include their impact on ecology and biodiversity, air pollution stemming from smoke and hazardous gases, effects on water and soil quality, influence on climate patterns and environmental pollution primarily arising from the residual ash. In summary, when considering both environmental and socio-economic factors, it becomes clear that bushfires present a significant and serious threat, and the management of these fires remains a formidable challenge.

The development of reliable and accurate bushfire management strategies is an urgent necessity to tackle the problem of increasingly frequent and severe bushfires. Fundamental elements of a bushfire management system encompass bushfire prediction, detection, suppression and prevention. Within the domain of bushfire prediction, efforts are focused on forecasting bushfire risk, the occurrence of bushfires, their spread and the resulting consequences. Generally, fire risk is assessed through the concept of “fire danger,” which is quantified using various fire indices. Different countries have established their own fire danger indices, considering the specific characteristics of their topography, vegetation and other relevant factors. Furthermore, meteorological variables, forest attributes and fire statistics are scrutinised to assess fuel characteristics and generate maps indicating the probability of fire occurrences and bushfire susceptibility. The spatial and temporal distribution of fire danger mapping plays a crucial role in identifying regions potentially prone to bushfires.

Advanced bushfire prediction and detection are primarily achieved by making use of satellite imagery, data from wireless sensor networks and information collected from UAVs. Past research indicates that automated algorithms developed using machine learning hold substantial potential for analysing and interpreting the gathered data. Each of these techniques has its own set of advantages and limitations. Satellite imagery, for instance, offers an excellent spatial resolution but tends to have a lower temporal resolution, particularly with Earth-orbiting satellites. Additionally, it can be challenging to mitigate the impacts of smoke and identify details in the forest understory when using this method. Furthermore, operating satellites demands a high technical expertise and entails significant expenses. Conversely, wireless sensor networks can help overcome the challenges associated with distinguishing the forest understory. Nonetheless, the need for a significant number of sensors distributed throughout the field remains imperative to adequately cover expansive forests when it comes to predicting and detecting fires. The potential of UAVs for bushfire management is evident from previous studies, especially considering the enhanced personal safety, extended operational coverage, reduced cost and swift manoeuvrability. However, the applicability of UAVs for bushfire management is impeded by constraints related to energy limitations, payload capacity limitations, as well as challenges associated with path planning and coordinating multiple UAVs. While placing the emphasis on aspects like bushfire prediction, detection and suppression, it is equally critical to incorporate preventive measures into the overall bushfire management strategy. Enhancing the resilience of structures to withstand bushfires, relocating assets to areas less prone to fires or with reduced exposure, and practicing responsible flame management are all key components to take into account. Irrespective of the robustness of bushfire prediction and detection algorithms, there always remains a residual probability of experiencing devastating bushfires. Therefore, having personal knowledge about escape routes and understanding how to protect oneself is crucial in order to minimise the potential for fatalities and injuries during bushfire events. Additionally, enhancing recovery and promoting adaptive behaviour is of utmost importance from a social standpoint.

A sustainable bushfire management framework for a given geographic area should be developed by integrating different bushfire management techniques, given each technique's relative advantages and disadvantages. For instance, relying solely on satellite imagery may not offer a viable solution for effective bushfire management. Conversely, when satellite imagery is combined with on-ground field sensors and information collected from UAVs, it has the potential to deliver improved bushfire prediction and detection accuracies. It is challenging to propose a simple, unique solution for bushfire management given the complexity of bushfires, considering the changing circumstances of landscapes, vegetation patterns, weather conditions and ecosystems. Therefore, it is imperative to conduct separate investigations in distinct geographic areas, pinpointing the influential parameters essential for crafting viable bushfire management strategies. Figure 6 illustrates an overall framework for bushfire management considering the aspects of bushfire prediction, detection, suppression and prevention. The optimal techniques for addressing various aspects of bushfire management should be chosen according to the resources accessible within a specific geographical area. Therefore, the most effective strategies for managing bushfires can differ from one country to another, and a single solution may not be universally applicable. The primary benefit of the proposed bushfire management framework lies in its capacity to rely on the advantages of various management strategies. This is because it integrates various techniques rather than concentrating solely on a single approach. Furthermore, the proposed framework allows for addressing the spatial and temporal variation in bushfire weather conditions while considering topographical attributes and fuel characteristics. This may lead to accurate bushfire detection and prediction. Nevertheless, employing multiple approaches can impose significant resource and financial demands. Therefore, it is essential to conduct a meticulous selection of the most appropriate combination of methods, with a strong emphasis on the allocated budget and available resources.

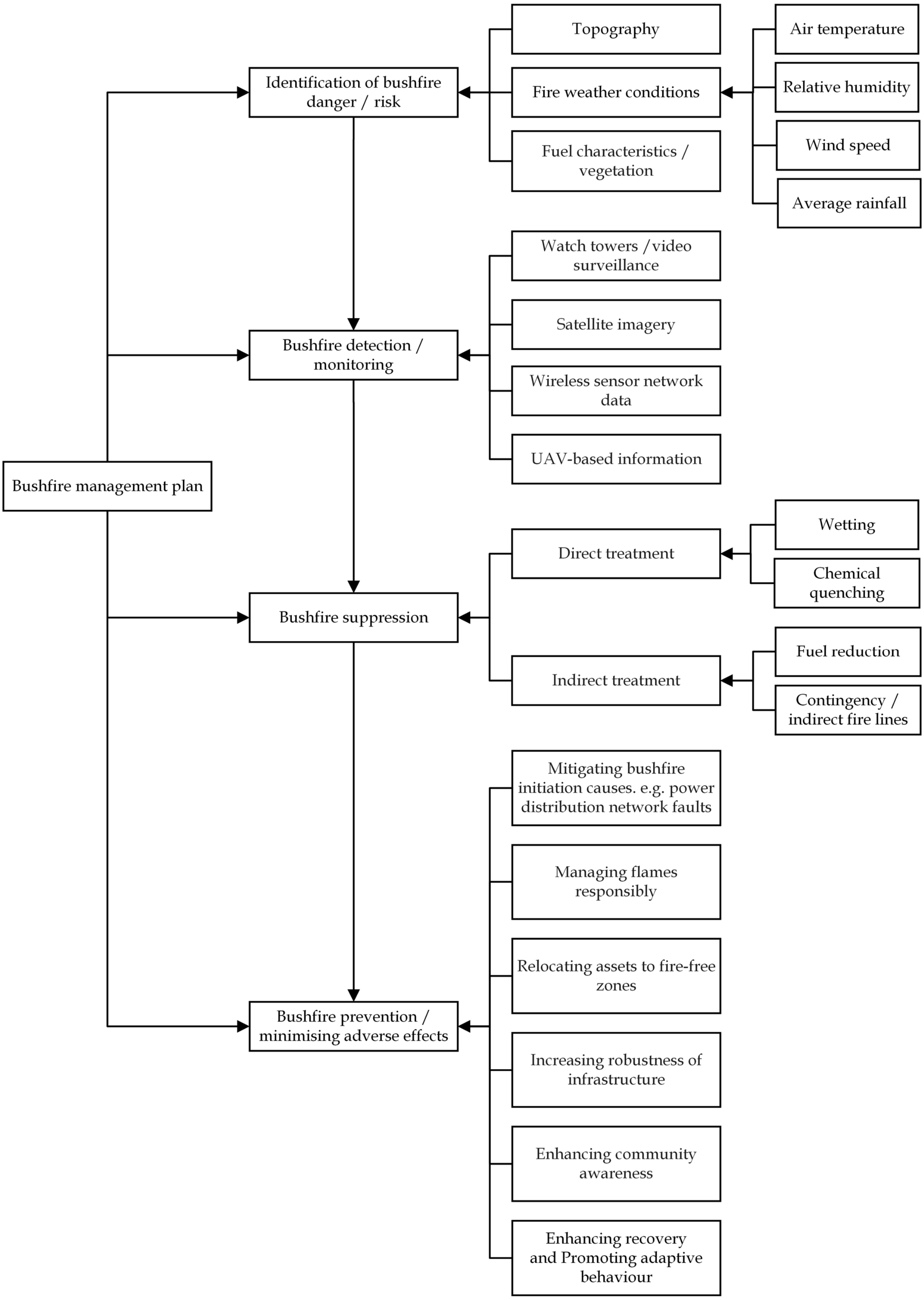

Figure 6. Framework for bushfire management.

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