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REVIEW ARTICLE

A theoretical framework for improved fire suppression by linking management models with smart early fire detection and suppression technologies

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Abstract Bushfires are devastating to forest managers, owners, residents, and the natural environment. Recent technological advances indicate a potential for faster response times in terms of detecting and suppressing fires. However, to date, all these technologies have been applied in isolation. This paper introduces the latest fire detection and suppression technologies from ground to space. An operations research method was used to assemble these technologies into a theoretical framework for fire detection and suppression. The framework harnesses the advantages of satellite-based, drone, sensor, and human reporting technologies as well as image processing and artificial intelligence machine learning. The study concludes that, if a system is designed to maximise the use of available technologies and carefully adopts them through complementary arrangements, a fire detection and resource suppression system can achieve the ultimate aim: to reduce the risk of fire hazards and the damage they may cause.

Keywords Forest fire · Resource suppression · Smart fire detection and suppression system · Forest fire management · Holistic system

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Introduction

From June 2019 to April 2020, Australian bushfires burnt more than 17 million hectares and destroyed more than 3000 homes (Bushfire and Natural Hazards CRC 2020). These devastating natural disasters highlight the urgent need for innovative technologies as well as new fire resource management systems.

Fire detection and suppression methods have been largely the same for many years, using people in fire towers for ignition reporting, and a map and pencil to pinpoint the location for its suppression. A smarter, more dependable detecting system is needed, using modern technologies such as cameras, sensors, satellites, robots and artificial intelligence. However, there are challenges with the associated costs, and there is a lack of confidence in the reliability of these technologies.

This study reviews the current technologies, management systems and management models used in bushfire detection and suppression and proposes a framework that uses the operations research method to bring existing fire behaviour modelling, geographic information system (GIS) applications and available ground-, space- and image-based fire detection technologies together into one fire decision-making framework for efficient resource management.

Current detection technologies and management systems

Early fire detection is an important control method and has been largely carried out using ground-based, space-based and computer image-based methods.

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Ground-based detection

For more than half a century, a 'person in a tower' has been used to detect forest fires. However, human observers are costly and there is a risk to human safety as well as property. In addition, fire towers have a limited lifespan and maintenance and replacement costs are high. Moreover, fire towers only contribute to fire detection within their surroundings, perhaps up to 50 km.

Video-based fire detection monitors identify the location of fires and provide an alert, but these technologies require advanced image processing (Çelik et al 2007; Vipin 2012; Çetin et al 2013). The German Aerospace Institute (DLR), as part of the NASA Mars Pathfinder Mission (NASA, 2014) have provided panoramic pictures at different magnification levels, which gives a warning and displays the fire location in a GIS.

Non-visual infrared- based wireless sensor networks (WSNs) (Bouabdellah et al. 2013) require advanced algorithms to improve communication speed and energy efficiency. Recently more technically advanced solutions, such as infrared visible light cameras and thermal imaging cameras, have been developed for fire detection, which require routing protocols for rapid data transmission (AL-Dhief, Sabri, Fouad, Latiff, Albader, 2019). Cetin et al. (2013) suggests that point sensors in WSNs can cause information delay, while video-based fire detection provides a volume of videos with timely and accurate information on fire size and growth. Integrating both non-visual and visual applications can reduce false alarms.

Manned and unmanned aircraft equipped with imagery sensors provide flexible fire detection by moving quickly to affected areas and spotting different fire occasions. Unmanned arial vehicles (UAV) have been used for forest fire detection, location and monitoring, but they have high costs, regulatory restrictions, and issues of robustness (Ollero et al. 2006). Discontinued remote-controlled flying quadcopter aircrafts have also been developed and are equipped with gas sensors and a thermal camera to fly to a fire and determine the origin of the reported fire location (Krüll et al 2012). Augmented Reality (AR) drones can reduce the number of false alarms than other detection systems and have a lower cost than manned aircraft, but they require a large power supply and can only carry limited weight. Table 1 lists some mainstream commercially available fire detection applications.

Recently smart firefighting robots or automated ground vehicles have attracted attention because they decrease risks to people firefighting and can increase their efficiency (Krasnov and Bagaev, 2012).

Space-based detection

Another fire detection technology currently in use are imagery sensors on Earth-orbiting satellite systems. These can detect fires on a global scale and monitor them on a frequent basis. They are particularly useful for post-fire assessments of damage, determining the area burnt and when it occurred. However, Parks (2014) found that, while satellite detection provides global coverage and reasonable temporal resolution, the coarse spatial resolution of freely available satellite imagery often prevents it from accurately determining the exact fire location. Various fire monitoring systems, such as Geoscience Australia's Digital Earth Australia (DEA) hotspots system, provide location and heat information. For example, this broad area training method extracts the expected diurnal cycle of a pixel using temporally rich data and has shown potential for use in fire detection. Hally et al (2019) used this method on the advanced Himawari Imager sensor pixels and detected positive thermal anomalies in up to 99% of cases based on low, Earth-orbiting satellite active fire products.

Satellite sensors provide observation and measurement data on fire hotspots, fire temperatures, actively flaming

Table 1 Ground-based sensor methods of fire detection applications

System	Range	Sensor type	Fire identification method	Source
AlarmEye	Unspecified	Video camera	Image colour analysis	https://www.austfire.com.au
EYEfi SPARK	Unspecified	HD video camera Thermal sensor lightning sensor	Human	https://www.eyefi.com.au
ForestWatch	Optimal 8–16 km max 40 km	Video camera	Image colour analysis	https://evsolutions.biz/forestwatch/
ADELIE	20 km in clear weather	Video camera	Image colour analysis	http://www.paratronic.info
Faedo	19 km	Video Camera	Image colour analysis	https://www.indracompany.com
Wildland Detection Systems	10 km	Video camera	Image colour analysis	http://www.wildlandsystems.com/index.html
Project VERSI	5–10 km	Thermal camera video camera	Thermal analysis Image colour analysis	http://www.sr7.eu/idiomas/ing/vigilancia_forestal.php
Firehawk	15-km radius	HD video camera	Image colour analysis	https://home.firehawk.co.za/

and smouldering fires, smoke, and gas emissions, burned areas and areas vulnerable to wildfire outbreaks. Zhukov et al (2005) demonstrated that the best sensors for space-based fire detection are those in the middle infrared part of the electromagnetic spectrum. Combining these with RGB (red, green, and blue) near infrared and thermal infrared spectral bands from other platforms, or even the same sensor platform, allows classification as well as an estimation of quantitative fire parameters. Satellite platforms are either on a near-polar orbit approximately 700 km from Earth or are geostationary (about 35,000 km away). Therefore, early detection of fires from space is limited due to the spatial resolution of geostationary satellite sensors (e.g., Himawari-8/9 AHI with 2 km for mid infrared) and the revisiting time of orbital satellite sensors (e.g., VIIRS of 12 h). Table 2 compares fire detection features of currently available satellite sensors.

Recent research approaches for early fire detection from space include detection of small fires with SWIR bands from high or very high resolution satellites, such as Sentinel-2, Landsat-8 and WorldView-3 (Liew 2021); Machine-Learning-based approaches such as for the detection of fire smoke (Zhao et al 2022; Zhao et al 2024a, b); and the use of CubeSat constellations or high-altitude platform systems (HAPS) to address gaps in spatial, temporal and spectral resolution (Tan 2020).

Nevertheless, no satellite system provides optimal characteristics for fire detection and monitoring; hence, combining various sensors is required to optimise use of current systems (Papaioannou et al. 2020). Moreover, due to limitations of each instrument, satellite imagery-based fire information is best used in conjunction with other methods such as fire towers and on-ground sensor networks (Jones et al 2017; Umar et al. 2017).

Underlying image-based fire detection algorithms and technologies

Modern fire detection systems analyse video frame images for the colour and shape of smoke and flames, but it is still a challenge for reliable identification because of their variability in shape, motion, transparency, colours, and patterns (Cetin et al 2016). Although source data can be provided by ground- and air-based camera sensors (from cameras mounted on observation towers or drones, respectively), the underlying detection technology still relies heavily on image colour analysis for long-range detection. The infrared thermal imaging application is usually effective only within a short distance.

Colour analysis is one of the oldest detection techniques used in video-based fire detection and is still used today in most detection methods. Most systems use RGB colour space, as many visible range cameras are in RGB format. The established rule is that flame pixels are RGB values with much larger pixel value differences ($R > G > B$) compared to smoke pixels that have RGB values close to each other (Cetin et al 2016). Recent research has improved colour analysis. For example, Vipin (2012) proposed a method to detect fire in images based on seven rules using both RGB and YCbCr colour space. Giwa and Benkrid (2018) created a conversion matrix for colour differentiation in an effort to reduce false alarms due to objects that have flame-like colours. Cruz et al (2016) developed a Forest Fire Detection Index to detect flames and smoke, especially in forested environments.

Since the visible spectrum (RGB colours) is associated with a distinct range of light wavelength (e.g., 650 nm for red), light spectrum analysis can also be used in fire detection. Dennison (2006) suggested that fire detection in shortwave infrared (SWIR) imaging spectrometer data was

Table 2 Satellite sensors suitable for fire detection

Jlv	Spatial resolution of respective relative bands	Revisit time	Latency	Information	Costs
Himawari-8/9 AHI	2 km	10 min	17 min*	Hotspots	Free
MODIS	500 m/1 km	1 day	10–30 min (NRT)	Hotspots	Free
AVHRR	1.09 km	12 h	10–30 min (NRT)	Hotspots	Free
Suomi-VIIRS	375/750 m	12 h	10–30 min (NRT)	Hotspots day and night band	Free
Landsat-7/8/9	30/60/100 m	8 – 16 days	Initial TIRS: < 12 h (avg 4–6 h) 2Tier1/Tier2: 14–26 days	Burned areas	Free
Sentinel-1 A/B	10 m	6 days	2–12 h (avg 5 – 6 h)	Cloud-free hotspots	Free
Sentinel-2 A/B	10/20 m	3 – 5 days	2–12 h (avg 5 – 6 h)	Burned areas	Free
Sentinel-3 A/B	1 km	1 day	2–12 h (avg 5 – 6 h)	Hotspots day and night band	Free
RadarSAT	3 m	1 day	4 h	Cloud-free burned areas	US$12/km^2
WorldView-3	0.37/1.24/3.7 m	< 1 day	n/a	Burned areas	US$58/k^2

*Himawari-8/9 based hotspots are loaded onto the sentinel hotspots platform approximately 17 min after acquisition time (in rare cases up to 30 min) possible using the proportion of reflected and emitted radiance absorbed by atmospheric carbon dioxide. In practice, special sensor devices such as spectrometers are used for this type of analysis.

Machine learning- based methods have recently been introduced to improve colour analysis to increase prediction accuracy and reduce false positives. Gunay et al. (2011) proposed a fire smoke detection method that uses adaptive decision fusion, on online learning framework that combines the results from its five sub-algorithms: slow-moving object detection, smoke-coloured region detection, wavelet transformation, shadow detection and elimination, and classification based on a co-variance matrix. Each sub-algorithm gives values between − 1 and 1 with weights adjusted.

By combining image colour analysis with other methods, such as infrared thermal analysis, vendors have released fire detection systems for commercial applications and the Convolutional Neural Network Analysis for better detect fire location (Frizzi et al 2021).

In summary, discontinued remote-controlled flying quadcopter (Drone) and GPS tools can be applied as image and position validation for more accurate point observation. Satellite data would be easily applied for fire detection once the technology is sufficiently developed; therefore, future research in analysing satellite image data is important.

Current fire management models

Fire behaviour models apply mathematical algorithms to analyse the relationships between burning conditions and important variables in the burning environment (Rothermel 1972; Alexander and Cruz 2013; Zazali et al 2020), such as fuel loading, wind velocity, temperature, humidity, slope, and solar aspect. Models are expected to predict fire behaviour, including fire initiation, propagation, and risks, to help fire managers and stakeholders to make fire suppression decisions, primarily functioned for fire prevention management.

Fire management factors

A fire management system can help agencies make decisions when there are conflicting objectives and uncertainty (Martell 2015). Suppression decisions can be complicated due to lack of access to the fire because of steep slopes or particular types of vegetation (McCarthy et al 2003), forest road and firebreak standards (Demir et al 2009) and fire access roads (Akay et al 2012), as roads directly impact fire control activities, different road function design is critical for wildfire management (Thompson et al 2021).

Fuel management strategies have been presented as mechanical (physical) fuel load removal, controlled (prescribed) burns and chemical treatments. Fernandes et al (2000) examined the effects of fuel management and suggested that, in a short-term fire management plan, prescribed burning and physically removing fuels effectively reduce fire hazards. Despite fuel conditions significantly affecting fire line construction rates, the costs of prescribed burns and fuel load removal are high, and further cost-effectiveness analysis is needed.

Martell (2001) suggested zone-based land management to reduce fire risk. First, the region should be partitioned into zones or compartments that are reasonably homogeneous with respect to forest ecosystems, land use patterns and values at risk. Next, the potential beneficial and detrimental impacts of fire in each zone should be assessed. The appropriate level of protection or fire regime for each should be selected and a plan developed to minimise the cost of achieving that objective. Finally, a fire management plan should be implemented, monitored, and revised over time.

About 72% of fires are caused by negligence or carelessness, such as from picnic fires, burning rubbish and cigarettes, while less than 3% were deliberately lit, 3.5% were accidental, 7% were from lightning and 15% were unknown causes (Demir et al 2009). They also suggested a number of strategies to reduce fuel along roadsides and railways and in recreational areas. Hence, area fuel reduction is carried out under silvicultural programs.

Dispatch travel model

After a fire ignition point is identified, fire trucks need to reach it from their standby locations quickly via the most optimal and safest road network. Based on graph theory, a GIS-based network analysis analyses the shortest arrival time by considering road lengths, fire truck speed, fire behaviour, vegetation, and population [by the likely level of communications network]. Graph theory requires a network incidence matrix and a set of linked impedance values to analyse all moves between the sets of origins and destinations (fire ignition points and suppression resource locations). Detailed information is found in Wilson and Wiitala (2005), Scott and Dunn (2015) and Taylor (2017).

Some researchers have applied a simulation model using GIS-based satellite imagery processing workflows. Bonazountas et al. (2007) developed a decision support system supported by GIS and Visual C + + technologies using a common user interface to produce an integrated computer system based on fuel maps from semi-automatic satellite imagery processing, socio-economic risk modelling and probabilistic models to manage fires. Linear programming models have been used to optimise resource allocation, especially for truck delivery (Dantzig and Ramser 1959; Vasic and Predic 2011). Discrete dynamic shortest-path algorithms have been used for ambulance allocation which can also be used to support equipment allocation in fire suppression.

Data analysis model

An understanding of the fire condition and behaviour is required for decisions that suit the characteristics of the fire for the most efficient fire management. Some of the models utilize predictions of fire behaviour; for example, the Phoenix Rapidfire model uses a range of environmental conditions and fire behaviour components to simulate fire behaviour and progression (Cruz et al 2014). They pointed out that the model is to 'make them respond to the dynamic nature of the interaction between the fire and its environment'. However, it has limitations of simulation models in general, as it did not clearly demonstrate the ability to present real fire propagation mechanisms and does not include fire detection, fire controlling routes and facility management tools.

Some models utilize machine learning considering various factors to analyze fire probability and occurrence. They incorporate spatiotemporal analysis to examine the impacts of fire on the environment and socio-economy (Vilar del Hoyo et al. 2011). Machine learning techniques, specifically the maximum entropy model (MaxEnt) and random forest model (RF), are employed to predict the habitat suitability of animals in situations where fires occur (Oliveira et al 2012; Tariq et al 2022). There are other similar simulation models such as AUSTRALIS which is designed as a predictive aid for bushfire response management and Aurora, a web-based fire spread map and community warning delivery system (Cruz et al 2014).

Supporting methods in fire detection and suppression

The fire suppression process encompasses operational fire management activities, including pre-suppression planning, initial fire assessments and initial attack dispatching, and is integrated into initial-attack containment models (Hirsch et al. 2004). The cost of crew members required for fire suppression, influencing cost-effective forestry land management, determines the necessary resources (Hirsch et al 2004). Efficient fire attack relies on accurate fireline estimations, often defined by the beta probability for a more precise prediction of fireline construction rate (Gilless and Fried 2000). McCarthy et al (2003) studied firefighting resource allocation and fireline construction rates to enhance construction predictions. They highlighted terrain, debris, and operator experience as primary factors.

Reducing bushfire risk rather than increasing suppression resources may be a better strategy (Morgan et al 2020), especially by using prescribed burning. Florec et al (2020) determined that in the south-west forested West Australia region, the most cost-effective controlled burn would be a 15% of the land as an optimal prescribed burning regime. The high coefficient value of each treatment size is bigger than 1500 ha and the cost per ha A$34. For 500–1500 ha, the cost to control a fire would be A$47 per ha.

The cost of implementing each technology would be a substantial amount up-front, but it is beneficial to government agencies and forest companies (Cetin et al. 2013). For example, fire alarms require management to analyse false alarm frequency and cost–benefit analysis but achieve a safer outcome (Marks et al 2017). For forest fire alarms, Elmas and Sönmez (2011) applied data fusion algorithms such as an artificial neural network, a Naive Bayes classifier, fuzzy switching, and image processing to form a data fusion framework to help form efficient strategies for firefighting.

In an international context, there is a disconnect between technical feasibility and firefighting management decision-making, mainly due to a lack of understanding of these techniques and their cost. There is a need to determine the right technology at the right cost to make correct decisions. The probability distribution of human-caused fire can use a Poisson distribution that can fit fire occurrence reasonably well, and the Markovian properties can help simplify fire management systems (Cunningham and Martell 1973).

Fire suppression strategies

To place the best resources at the right fire location in fire suppression management, it is important to first look at landscape information with regards to fuel type, route map (minimum travel time), water points, fire behaviour with regard to moisture, wind speed and direction, the facilities available (fire crews, tankers, trucks, aircraft and to whom they belong) and the fire management program (Martell 2007). Some of the traditional methods of dealing with fire have been redirected such as prescribed burning (Morgan et al 2020).

Calkin et al (2005) suggested including drought factors into fire suppression expenditure decision making, assessing the possible beneficial and detrimental impacts of fire in each zone, selecting an appropriate level of protection for each zone and developing a plan to minimize the cost of achieving that objective, and implementing, monitoring, and revising the fire management plan over time.

In their study of the stochastic Weibull models and negative exponential models, Johnson and Wagner (1985) suggested that the fire cycle, annual burned area percent, average age of the vegetation and renewal rate are important in estimating pre- and post-fire suppression distributions.

Many current models tend to be one or two function focused. They are compartmentalized in each of the operations or scarcely able to systematically analyse for fire detection and suppression decision- making. There needs to be a holistic system that enables all the data from different technologies to function together.

Integration of simulation and real time detection system

Fire detection and suppression systems can be integrated into new technologies such as those mentioned previously and in UAV and other automated facilities to result in feasible operation procedures for management (Ollero et al. 2006). For a more efficient system to respond to and extinguishes fires, additional tools should be deployed to determine fire location, and facilities to access the fire for extinguishing. Cetin et al. (2013) identified important aspects to put into an integrated system: having the right equipment in the right place; being able to access to the most capable tools to assist suppression; having an accurate, up-to-date management view of the fire (e.g., wind direction, speed and other weather conditions, fire direction and growth rate); being able to forecast fire size, speed and direction; and making the best resource allocation decisions (e.g., whether to send two firefighters in an SUV or a C-5 aerial flame suppression tanker).

Martell (2015) noted that a fire management system can be viewed from a supply chain management perspective and defined as delivering 'the right amount to the right fire at the right place at the right time and right cost'. Fire managers operate in a highly challenging decision-making environment characterised by complexity, conflicting objectives, and uncertainty.

Current fire decision management systems are mostly focused on firefighting decision-making or fire spreading simulation and ignore modern and renewed fire detection technologies and integration of all relevant functions. Using operations research methods to combine fire detection technology and resource management decision-making can improve both resource use and time efficiency.

Operations research

Victoria Minas, Hearne, Handmer (2012) discussed different operations research methods, referred to as operations research (OR)/management science by Martell (2015), enabling analysis of interactions between people, resources, and the environment to aid decision-making in complex systems such as fire detection and resource suppression.

Operations Research is a discipline that utilizes mathematical and analytical methods to enhance decision-making processes and address intricate problems. It employs a scientific approach and applies quantitative techniques to improve decision-making. The primary objective is to leverage applied mathematics such as data modeling and linear programming, (e.g., Vilar del Hoyo et al. 2011), to tackle complex resource optimizations such as multi-point fire extinguishing.

OR methods encompass a spatial platform such as the R-ArcGIS bridge which addresses challenges related to travel time and resource location. GIS technology empowers modelers to consider real travel time or estimated travel time based on historical travel data, enhancing network efficiency. It can combine with other methodologies, such as R language, to consider large amounts of information or use a linear program model to monitor resource allocation at multi-fire locations. It also can include other factors such as road conditions, land information and multiple fire-related weather indicators. In addition, GIS systems can link with other fire detection technologies, such as using sensors and drones, to accurately report, reconfirm and indicate fire location.

Other studies have applied GIS systems and raster imagery data into a simulation model. Bonazountas et al (2007) used a GIS network analysis tool, employing spatial analysis to calculate travel time, in the same way as described by Wilson and Wiitala (2005), where roads were converted into raster cells. An accumulated access map provides travel time to each given raster cell.

A new framework

The proposed optimised fire suppression decision-making framework has four components: fire forecasting and prevention, detection, initial attack, and continuous attack and monitoring (Fig. 1).

Fire forecasters may use different types of tools such as satellite sensors that can provide heat maps or ground-based sensors providing temperature, humidity, and wind data to warn of fire hazards. However, prevention methods, such as controlled burns and removal of fuel, can efficiently reduce fire danger. Although prevention measures may effectively reduce fire hazards, they can be costly, and a cost–benefit analysis is needed.

Fire detection systems identify sources of heat, smoke, and flames. Historically, a person working in a fire tower had been the preferred way to detect forest fires. In recent years, detection methods have been advanced by satellite, camera, sensor technologies and machine learning analysis. However, every technology has its disadvantages, so it often is better to combine different technologies (e.g., satellite, drones, tower cameras) and use smart data management to detect fires faster and identify the ignition point.

Detecting the initial fire ignition is vital. Once this is confirmed, the quickest decision on equipment, crew members, transport routes and defining the fireline will help stop the fire spreading. A GIS-based platform can perform

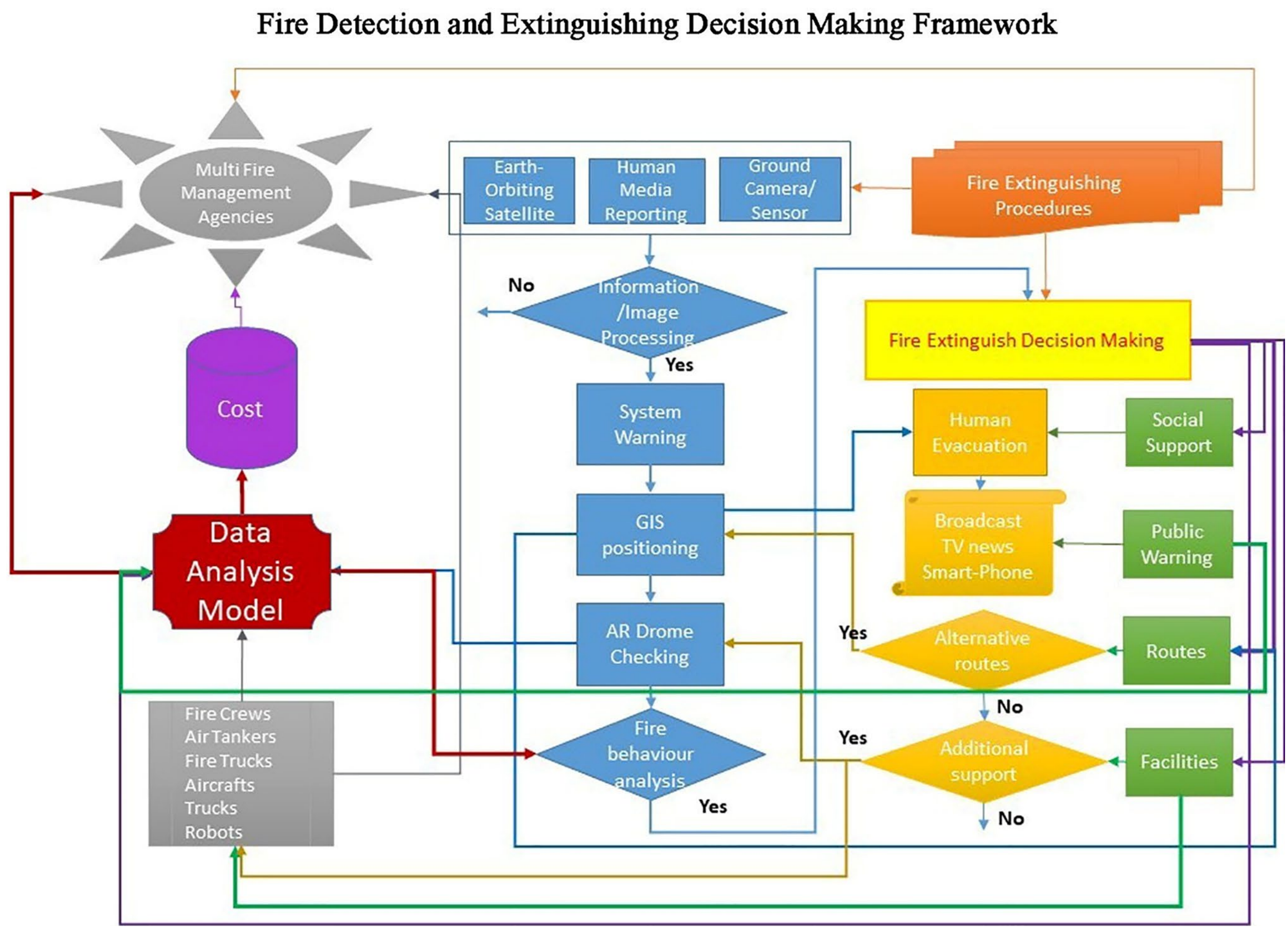

Fig. 1 Fire suppression decision-making framework

spatial analysis using road network data, water features, terrain models and land use to provide information for efficient decision-making.

Fire continuous monitoring is based on a simulation model that brings together information on temperature, wind, fuel levels and humidity to inform fire behaviour. This can be further extended to estimate the cost of using external resources and the introduction of an on-site monitoring system such as a camera. Figure 2 illustrates a combined technology system for smart fire detection, including human media reporting, camera and drone monitoring, and sensor and satellite systems. Advanced technology such as artificial intelligence can be introduced for increased warning and therefore increase fire detection accuracy. The current framework only addresses certain technologies, and there is a lack of coherence.

The development of a holistic framework requires the efforts of numerous stakeholders, including federal and state government policymakers, country fire services, forest growers, farmers, researchers, and communities. This collaboration is often lacking in existing frameworks.

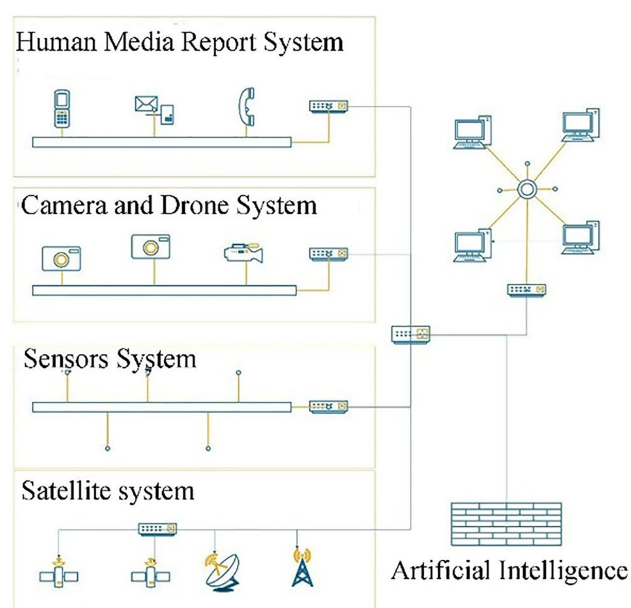

Fig. 2 Resources involved in the fire suppression system

There needs to be more effort to join different methods and stakeholders together in the system and to implement and updated it with new technology.

Green triangle region case study

The developed framework can significantly contribute to an advanced fire detection and suppression system. This study focused on the Green Triangle region of South Australia and Western Victoria, encompassing some 350,000 hectares of tree plantations with an estimated value of approximately AUS $3.0 billion. The region is equipped with multiple fleet trucks, water bombing aircraft and helicopters, and seven fire towers managed by Forestry SA in South Australia's southeast on high-risk days to report smoke and potential fires.

The current problem revolves around decisions to continuously update the fire towers or to transition to an automated fire detection system. Presently, the existing framework is a combination of traditional operational systems and some partial automated ones. It consists of a fire tower report (for high fire risk days) and telephone reports (on non-high fire risk days). Additionally, a fire behaviour estimation system, Phoenix, used for fire behaviour estimation and economic analysis, is part of the framework. Various spatial tools like ArcGIS and other software applications are employed for fire-related analysis.

For Mt. Gamier, it is crucial to periodically establish an automated fire detection system, considering that the forest owners and ForestrySA are actively seeking solutions for reducing detection cost on fire tower and decision-making for better detection.

(1) Implementing a human telephone report system, enhancing it with automated positioning and confirmation technologies for efficiency.
(2) Establishing and monitoring sensor points to form a reliable network, enabling analysis and warning functions.
(3) Utilizing satellite data (DEH hotspots) for space-based fire detection, forecasting, and detection improvement; current satellite sensor data still do not provide sufficient spatial, temporal, and spectral resolution to detect small fires; early detection is far from less than an hour).
(4) Continuing to use data analysis model-Phoenix Rapidfire for fire behaviour and economic analysis, with a potential extension into machine learning.
(5) Incorporating drones to confirm fire warning information and predict fire behaviour adjustment; the drone has limitations such as battery capacity and the restricted application within Australia within governing legislation.
(6) Employing machine learning to enhance fire detection algorithms, including smoke detection and sensor fusion, for improved precision and accuracy.

A data analysis model, Phoenix Rapidfire, has been used for fire behaviour and economic analysis. The model consists of a fire management business component, a fire characterization component, and a fire impact component. The model provides a relative measure of any combination of these elements in terms of bushfire risk:

(1) Calculate the point rate of spread, flame height, and fire line intensity;
(2) Estimate the physical "impact" of the fire on specified values and assets;
(3) Provide this information in a form that can be used to assess the consequence of these impacts (Tolhurst et al. 2008).

The stakeholders of the Green Triangle have expressed a desire for an automated fire detection and suppression system that is more risk-based and cost-effective, enabling early suppression responses. Using Phoenix Bushfire Modelling to estimate fire losses under a range of fire scenarios helps identify the costs of changes to detection times in terms of average annual loss and potential maximum loss from single fires. A loss of planation assets to a bushfire is calculated by the time taken to detect the fire, the time to despatch fire crew and travel time, and considers fuel, fire history, occurrences, types and the resources available. Table 3 shows a summary of fire impacts in terms of 95th percentiles, maximum values and averages. These are available for areas of plantation burnt, value loss, and standing value for each scenario, plantation type, detection time and weather. The Phoenix Bushfire Model provides a guide to maximum potential loss from a single fire but does not consider the likelihood of multiple fires.

The proposed framework integrates insights from the outcomes of Phoenix Rapidfire and incorporates data analysis models like AUSTRALIS and Aurora. Drawing from the current practices in the Green Triangle area, this project formulated an evaluation table that assesses the current status of the automated fire detection and suppression system, focusing on five key fire components: identification, confirmation, location, firefighting route choice, and decision-making for resource allocation. The proposed evaluation is also informed by the most recent literature, encompassing matrix information detailing the stages of fire suppression and the technologies applied. This includes data collection spots, data analysis models, GIS applications, and cost estimations (Table 4).

Based on this framework, appropriate technologies can be selected and combined to create a feasible and reliable

Table 3 95th percentile, maximum and average area burnt/value lost/standing value of plantation burnt/impacted

Plantation type	Scenario name	Weather scenario	Area burnt 95th percentile	Value loss 95th percentile	Standing value 95th percentile	Area burnt maximum	Value loss maximum	Standing value maximum	Area burnt average	Value loss average	Standing value average
Hardwood plantation	5minDet	BS	1399	$15,895,200	$23,835,600	3681	$44,439,000	$65,820,000	299	$3,310,000	$4,916,000
Hardwood plantation	5minDet	CR	958	$11,013,300	$16,391,800	3040	$36,306,000	$55,108,000	198	$2,226,000	$3,320,000
Hardwood plantation	5minDet	EXT	400	$5,713,230	$8,569,850	1428	$19,132,000	$29,649,000	95	$1,083,000	$1,609,000
Hardwood plantation	5minDet	SEV	667	$8,032,830	$12,196,700	1673	$24,348,000	$36,770,000	163	$1,957,000	$2,923,000
Hardwood plantation	5minDet	VH	121	$1,422,590	$2,133,880	415	$6,109,000	$9,163,000	23	$264,000	$392,000
Hardwood plantation	10minDet	BS	1368	$16,182,700	$24,671,000	3652	$41,787,000	$63,707,000	301	$3,316,000	$4,930,000
Hardwood plantation	10minDet	CR	901	$10,664,600	$15,994,800	2350	$32,555,000	$49,734,000	198	$2,235,000	$3,325,000
Hardwood plantation	10minDet	EXT	447	$5,985,610	$8,978,420	1478	$16,461,000	$24,583,000	106	$1,234,000	$1,838,000
Hardwood plantation	10minDet	SEV	702	$8,125,350	$12,196,700	1778	$25,096,000	$38,228,000	170	$2,043,000	$3,051,000
Hardwood plantation	10minDet	VH	123	$1,489,580	$2,234,360	518	$7,773,000	$11,659,000	25	$284,000	$423,000
Hardwood plantation	20minDet	BS	1396	$15,959,200	$24,060,200	3545	$44,477,000	$68,509,000	319	$3,529,000	$5,242,000
Hardwood plantation	20minDet	CR	975	$11,376,200	$17,232,500	3001	$40,890,000	$62,741,000	216	$2,424,000	$3,609,000
Hardwood plantation	20minDet	EXT	493	$5,985,610	$8,978,420	1505	$20,886,000	$31,328,000	119	$1,368,000	$2,042,000
Hardwood plantation	20minDet	SEV	755	$9,110,910	$13,495,900	1690	$24,607,000	$37,157,000	190	$2,260,000	$3,379,000
Hardwood plantation	20minDet	VH	160	$1,945,410	$2,918,120	392	$4,759,000	$7,139,000	29	$336,000	$502,000
Softwood plantation	5minDet	BS	5093	$24,760,900	$89,161,000	13,529	$67,378,000	$251,622,000	1122	$5,425,000	$19,013,000
Softwood plantation	5minDet	CR	3764	$19,048,800	$69,884,300	11,110	$58,234,000	$200,142,000	843	$4,116,000	$14,469,000
Softwood plantation	5minDet	EXT	1545	$8,687,830	$30,874,100	5811	$32,260,000	$107,499,000	352	$1,738,000	$6,187,000
Softwood plantation	5minDet	SEV	1887	$10,180,600	$34,428,800	4968	$23,753,000	$79,637,000	427	$2,167,000	$7,535,000

Table 3 (continued)

Plantation type	Scenario name	Weather scenario	Area burnt 95th percentile	Value loss 95th percentile	Standing value 95th percentile	Area burnt maximum	Value loss maximum	Standing value maximum	Area burnt average	Value loss average	Standing value average
Softwood plantation	5minDet	VH	456	$2,731,930	$8,927,620	1499	$9,117,000	$29,675,000	101	$540,000	$1,766,000
Softwood plantation	10minDet	BS	5199	$25,422,100	$89,665,800	13,157	$66,488,000	$230,601,000	1200	$5,767,000	$20,339,000
Softwood plantation	10minDet	CR	4229	$20,548,900	$77,273,600	12,267	$62,119,000	$207,152,000	923	$4,468,000	$15,794,000
Softwood plantation	10minDet	EXT	1697	$9,151,150	$33,431,600	5493	$29,188,000	$97,747,000	386	$1,910,000	$6,846,000
Softwood plantation	10minDet	SEV	1901	$10,376,300	$34,695,800	5724	$28,116,000	$90,697,000	442	$2,248,000	$7,842,000
Softwood plantation	10minDet	VH	489	$3,050,080	$9,305,050	1487	$9,206,000	$30,151,000	112	$594,000	$1,963,000
Softwood plantation	20minDet	BS	5804	$27,778,000	$102,043,000	14,361	$72,514,000	$258,797,000	1305	$6,253,000	$22,064,000
Softwood plantation	20minDet	CR	4513	$21,472,500	$78,607,500	11,601	$59,251,000	$208,836,000	1021	$4,911,000	$17,333,000
Softwood plantation	20minDet	EXT	1837	$9,905,480	$36,870,800	5111	$27,657,000	$93,191,000	445	$2,197,000	$7,826,000
Softwood plantation	20minDet	SEV	2072	$11,005,500	$36,702,200	5045	$23,888,000	$82,954,000	498	$2,492,000	$8,860,000
Softwood plantation	20minDet	VH	576	$3,440,300	$11,193,500	1647	$9,748,000	$32,094,000	133	$701,000	$2,333,000

Table 4 Evaluation table of the fire suppression and modelling system

Fire detection	Fire suppression resources	Original data sources	Data analysis model: phoenix rapidfire	ArcGIS platform	Cost
Generation of hotspots					
Fire forecast and prevention	Satellite	Online inform	Used for fire forecast		High
	Fuel management: controlled burn pruning and agroforestry (grazing control of fuel)	Planning and scheduling	Used for fire management and loss prediction		Middle
	Facility improvement (airtanker, robots) crew member and training	Planning and investment	Used for fire management and loss prediction		High
	Land planning: transport and firebreak system	Planning document	Used for fire management and loss prediction	Travel time calculation	Low
Identification of ignition point					
Fire detection: checking hotspots within 20 min	Camera system AR drone confirmation	Video information and GIS	Fire ignition point, fireline estimation	Fire location detection	Middle
	Sensors (theorem, smoke, flame)	System signals and GIS		Fire location detection	Low
	Human online report	Descriptive information Pictures		Faulty report filtering	Low
	Human tower	Phone call		Fire location confirmation	High
Decision for initial attack					
Fire initial attack: travel time and attack time within 30 min	Transportation and GPS	Road map and transport monitoring		Transport and time calculation	Low
	Fire suppression equipment and robots	Equipment supply		Resource transportation	High
	Human crew	Human resource supply		Resource allocation	Middle
	Suppression necessities	Resource supply	Resource supply	Resource supply	Low
Decision for clean up					
Fire continuous-attack and monitoring	AR drones	Video information and GIS		Fire monitoring and report	Low
	Camera as secondary information?	Video information and GIS		Fire monitoring and report	Low
	Any on-site monitoring system?	Monitoring data		Fire location monitoring	Middle
	Human inspections	Documents	Fire loss		Middle

next-generation fire detection solution. For example, an ArcGIS-based platform could overcome some of the disadvantages of the Phoenix bushfire model and improve other aspects of bushfire-related management. Fire suppression would consider cost allocation between modern detection systems, land management, human resources, equipment, and the fire detection system as a whole to seek an optimised solution.

While the integration of high-altitude pseudo-satellite (HAPS), unmanned aerial vehicles (UAVs), both aerial and around based, and sensor-based fire detection systems is on the horizon, challenges persist. Testing for reliability is expensive and effective stakeholder management is crucial due to the potential for different priorities of private ownership of plantations. Consequently, a clear operation procedure must be developed and continually devoted to the establishment of an automated fire detection/distinguishing system.

Conclusions

Using the Green Triangle as a case study, this paper shows that forest fires pose a high risk to the plantation forest industry and communities. In comparison to the high cost associated with the current human fire detection method, an integrated fire resource suppression system can encompass fire detection and suppression measures. New technologies such as online media, smart cameras, sensors, satellites, and artificial intelligence can be used for an advanced fire detection system, and existing fire simulation technologies such as the Phoenix Rapidfire can be used for fire behaviour simulation and cost estimations. All the information can be further imported into a GIS for fire suppression decision-making. At the same time, other supporting technology, such as GPS data resources, should be utilized in the firefighting fleets optimization decision- making. Some recent study has included include the transitional way and modern method and Artificial learning (Zhao et al. 2024a, b). An automated fire detection and suppression system should be developed to improve fire-related information transfer and exchange for greater efficiency.

When making decisions about fire suppression, estimating detection time and travel time is challenging. Currently, there are applications to develop an integrated and smart fire detection and resource suppression system equipped with artificial intelligence and image processing technology. In such an approach, validation for the system output is necessary utilizing AR drone, GPS data and satellite images.

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