Natural Hazards (2025) 121:9777–9800
https://doi.org/10.1007/s11069-025-07163-w

ORIGINAL PAPER

Active wildfire detection via satellite imagery and machine learning: an empirical investigation of Australian wildfires

Harikesh Singh[1,2] · Li-Minn Ang[1] · Sanjeev Kumar Srivastava[1]

Received: 13 August 2024 / Accepted: 28 January 2025 / Published online: 6 March 2025

Abstract

Forests worldwide play a critical role in biodiversity conservation and climate regulation, yet they face unprecedented challenges, particularly from wildfires. Early wildfire detection is essential for preventing rapid spread, protecting lives, ecosystems, and economies, and mitigating climate change impacts. Traditional wildfire detection methods relying on human surveillance are limited in scope and efficiency. However, advancements in remote sensing technologies offer new opportunities for more efficient and comprehensive detection. This study highlights the integration of satellite sensors, capable of detecting thermal anomalies, smoke plumes, and vegetation health changes, with machine learning, particularly Support Vector Machines (SVMs), to enhance detection efficiency and accuracy. These algorithms analyse satellite data to identify fire patterns and provide near real-time alerts. SVMs' adaptability over time improves performance, making them suitable for evolving fire regimes influenced by climate change. Focusing on the Wolgan Valley in Eastern Australia, the study utilised Landsat-8 imagery and SVMs to detect active fires and classify burned areas. Results demonstrated that combining various spectral bands, such as the Shortwave Infrared (SWIR) and Near-Infrared (NIR), enhances the identification of active fires and smoke. The introduction of the Normalized Difference Fire Index (NDFI) further refines detection capabilities by leveraging distinct spectral characteristics from Landsat 8 imagery. Despite the promise of these technologies, challenges such as data availability and model interpretability remain. Future research should focus on integrating diverse data sources, advancing machine learning techniques, developing real-time monitoring systems, addressing model interpretability, integrating unmanned aerial vehicles, and considering climate change impacts. This study underscores the potential of machine learning algorithms and innovative indices like NDFI to improve wildfire detection and management strategies, ultimately enhancing our ability to protect lives and ecosystems in fire-prone regions.

Keywords Active fire detection · Landsat-8 imagery · SVM · Machine learning · Normalized difference fire index (NDFI)

Extended author information available on the last page of the article

1 Introduction

Forests worldwide serve as critical protectors of biodiversity and vital regulators of our climate. However, in recent decades, they have encountered an unparalleled series of challenges, which have raised doubts about their future (Garcia et al. 2020). This era has witnessed a remarkable surge in scientific discourse, with a pronounced focus on climate change and its numerous environmental impacts (Abbass et al. 2022). In this conversation, wildfires have emerged as a particularly alarming concern, capable of causing extensive destruction on both a global and regional level. (Eliott et al. 2021; Srivastava et al. 2013). Therefore, the urgent need to detect wildfires early and closely monitor their features across expansive areas has become increasingly critical.

Early detection of wildfires is crucial due to its potential to prevent the rapid spread of fire, protect lives through timely evacuation efforts, preserve biodiversity by minimising habitat destruction, maintain air quality by reducing smoke emissions, mitigate economic losses by minimising property damage and firefighting costs, optimise resource allocation for firefighting efforts, and contribute to climate change mitigation by reducing greenhouse gas emissions (Singh et al. 2024). By promptly identifying wildfires, communities can take swift action to mitigate their impact, safeguarding both human and ecological well-being while minimising long-term consequences on the environment and economy.

Historically, wildfire detection relied heavily on human surveillance, often from observation towers or through patrols in high-risk areas (Dalezios et al. 2017). These individuals, armed with basic tools like the Osborne fire finder, surveyed the horizon for any indications of smoke or fire, acting as the primary defence against the destructive forces of wildfires (Guth et al. 2005). Nevertheless, this system faced inherent constraints such as human mistakes, restricted visibility in harsh weather, and the incapability to offer immediate coverage over vast areas.

The advancement of remote sensing technologies offered a glimmer of hope in the pursuit of more efficient and comprehensive wildfire detection. Satellites equipped with sensors capable of detecting various indicators associated with wildfires, including thermal anomalies, smoke plumes, and changes in vegetation health, revolutionised the monitoring landscape (Chuvieco et al. 2019). These satellites, orbiting high above the Earth's surface, provided unparalleled coverage and spatial resolution, enabling the detection of wildfires in remote or inaccessible areas.

Among the most common satellite indices used for fire detection is the Fire Weather Index (FWI), which assesses fire risk based on weather conditions such as temperature, wind speed, and humidity (Pérez-Sánchez et al. 2017). While effective for weather-based risk assessment, FWI does not directly leverage satellite imagery for real-time fire detection (Chuvieco et al. 2023). Similarly, the Fire Radiative Power (FRP) index estimates the intensity of a fire using thermal infrared data, providing crucial information about the energy released from biomass combustion. While effective for detecting large, intense fires, FRP may miss smaller or less intense fires, particularly in forested regions (Wang et al. 2020).

In this study, a novel Normalized Difference Fire Index (NDFI) is introduced, focusing on differentiating burned and unburned areas based on spectral reflectance in the SWIR 2 and red bands. The NDFI, unlike other indices such as the Normalized Burn Ratio (NBR) or the Differenced NBR (dNBR), offers a unique approach by utilizing these specific spectral bands to enhance fire detection accuracy, especially in areas with varying vegetation and topography. The NBR and dNBR are widely used for mapping burn severity, analysing pre- and post-fire satellite imagery. While both indices are useful, they may struggle to detect fires under dense canopies or small fires that emit minimal thermal radiation. The NDFI, on the other hand, addresses these challenges by providing better sensitivity to fire-affected areas, making it particularly valuable for detecting smaller fires and accurately delineating fire boundaries.

Moreover, indices such as the Burned Area Index (BAI), Global Environment Monitoring Index (GEMI), and Mid-Infrared Burn Index (MIRBI) focus on vegetation stress, active fire, or smoke detection through various spectral bands (Ba et al. 2020). Each index emphasizes different aspects of wildfire detection, offering trade-offs between precision, temporal resolution, and data availability.

However, the sheer volume of data generated by satellite sensors posed a formidable challenge. Traditional methods of analysing satellite imagery relied on manual interpretation by trained experts, a labour-intensive process prone to errors and inconsistencies (Carling et al. 2008). Moreover, the dynamic nature of wildfires, with their rapidly changing behaviour and spatial extent, rendered static analysis techniques ineffective in capturing their full complexity.

In response to these challenges, the field of machine learning emerged as a promising avenue for advancing wildfire detection capabilities. By leveraging the power of artificial intelligence to analyse vast amounts of satellite imagery, machine learning algorithms could identify patterns and anomalies associated with wildfires with unprecedented speed and accuracy (Varsha et al. 2024). These algorithms, trained on large datasets of labelled imagery, learned to differentiate between normal environmental variations and the distinctive signatures of wildfires, enabling them to detect fires in near real-time and provide early warnings to emergency responders.

One of the key advantages of machine learning-based wildfire detection systems is their ability to adapt and evolve over time. As new data becomes available and the algorithms encounter novel scenarios, they can refine their understanding of wildfire dynamics and improve their detection capabilities (Mohapatra and Trinh 2022). This adaptability is particularly crucial in the context of climate change, where shifting environmental conditions and emerging fire regimes pose ongoing challenges to traditional monitoring methods.

In recent years, researchers have made significant strides in developing machine learning algorithms specifically tailored to wildfire detection. Among these algorithms, Support Vector Machines (SVMs) have emerged as a particularly promising approach due to their ability to effectively handle high-dimensional data and nonlinear relationships (Kar et al. 2024). By integrating multiple data sources, including satellite imagery, weather data, and historical fire records, SVMs can generate probabilistic wildfire risk maps, aiding authorities in prioritizing resources and allocating firefighting assets more effectively (Dhall et al. 2020; Thompson et al. 2019).

While machine learning-based wildfire detection systems offer considerable promise, they are not without their challenges and limitations. One of the primary challenges is the availability of high-quality training data. Machine learning algorithms rely on labelled training data to learn the patterns associated with wildfires, and acquiring such data can be challenging, particularly in regions with limited historical fire records or sparse ground-truth observations (McCarthy et al. 2021). Moreover, satellite imagery can be prone to errors and artifacts, which can adversely affect the performance of machine learning models if not adequately addressed. Ensuring the reliability and accuracy of training data is, therefore, essential to the success of machine learning-based wildfire detection systems.

Another challenge is the interpretability of machine learning models. While these models can achieve remarkable levels of accuracy in detecting wildfires, understanding how they arrive at their decisions can be challenging, particularly for complex algorithms like SVMs (Jain et al. 2020; Singh et al. 2024). This lack of interpretability can hinder the adoption of machine learning-based wildfire detection systems in operational settings, where stakeholders require transparency and accountability in decision-making processes (Kyrkou et al. 2022; Sos et al. 2023). Addressing this challenge requires the development of explainable AI techniques that can provide insights into the inner workings of machine learning models and enhance their trustworthiness and utility.

Despite these challenges, the integration of satellite imagery and machine learning algorithms, particularly SVMs, holds tremendous promise for revolutionising wildfire detection and management. By harnessing the power of artificial intelligence and remote sensing technologies, we can enhance our ability to detect active wildfires, mitigate their impacts, and protect both human lives and natural ecosystems (Singh et al. 2022a, b, 2024). This empirical investigation seeks to explore the efficacy and potential applications of SVM-based wildfire detection systems within the context of Australian wildfires, offering insights into their performance and feasibility in real-world settings.

2 Materials and methods

2.1 Study area

Australia, renowned as the sixth-largest nation globally in terms of total area, dominates Oceania as its largest country. With a population of twenty-six million, the majority of inhabitants are concentrated along the eastern seaboard. This vast country is characterised by semiarid and arid regions, covering between 50 and 75% of its landmass (Fujioka and Chappell 2010).

Our study focuses on the vicinity of the Wolgan Valley near Lidsdale in Eastern Australia, an area that endured significant wildfire activity during in December 2019 (Fig. 1). This region was specifically chosen due to the site of one of the largest wildfires in New South Wales in 2019 (Krogh et al. 2022; Singh et al. 2022a, b). This event severely impacted the region, including the Blue Mountains National Park, Gardens of Stone National Park, and Wollemi National Park, as well as nearby areas. The devastating forest fire incident of 2019 wreaked havoc on the region's flora and fauna and significantly impacted air quality (Singh et al. 2022a, b). Situated within the New South Wales (NSW) region of Lithgow, Wolgan Valley is nestled along the banks of the Wolgan River, approximately 32 km north of Lithgow and 150 km northwest of Sydney.

Access to Wolgan Valley is facilitated by the Castlereagh Highway, leading to the Wolgan Valley Discovery Path (Wolgan Route). This scenic route guides travellers through the valley, showcasing the historic Newnes region, renowned for its extensive industrial ruins. The route continues eastward, tracing the path of the Wolgan River until it meets the Capertee River and eventually the Colo River.

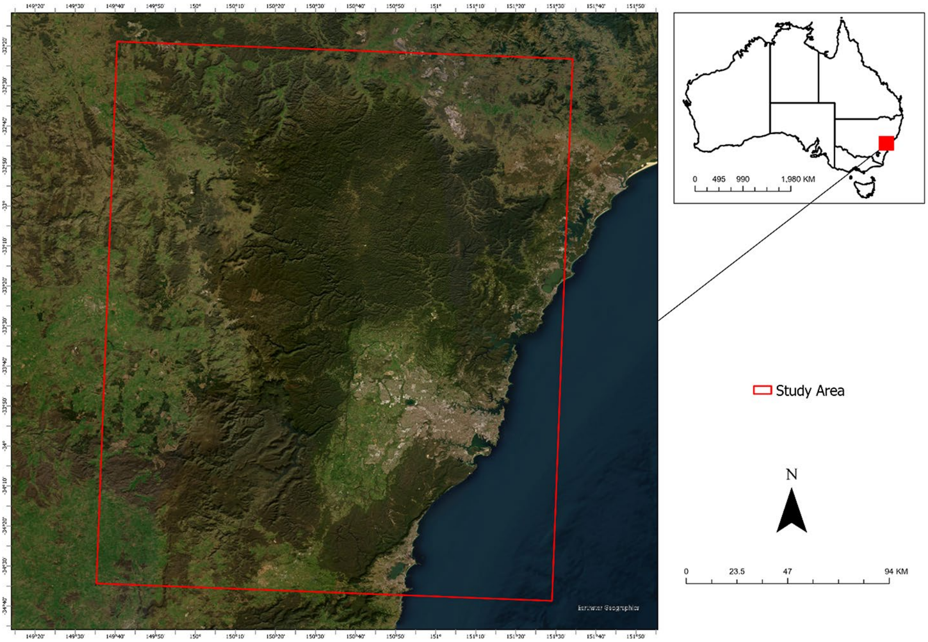

Fig. 1 Location of the study area. wolgan valley, near lidsdale, eastern Australia, highlighted on a satellite imagery background

Wolgan Valley is encompassed by the Wollemi Wilderness, serving as the largest protected area in New South Wales and Eastern Australia. This vast expanse, spanning 361,000 hectares, is a sanctuary for biodiversity and natural heritage. Within the Wolgan Valley lies Wollemi National Park, Stone Gardens National Park, and the UNESCO World Heritage Region of Blue Mountains. These protected areas are renowned for their rugged beauty, ancient rock formations, and diverse ecosystems.

However, the serenity of Wolgan Valley was shattered in December 2019 by a devastating forest fire incident, which wreaked havoc on the region's flora and fauna and significantly impacted air quality. The aftermath of this wildfire serves as a stark reminder of the importance of implementing robust wildfire detection and monitoring strategies to safeguard the ecological integrity of Wolgan Valley and its surrounding areas.

2.2 Methods and datasets

The proposed methodology for forest fire detection utilises a novel model combining Support Vector Machines (SVM), applied to Landsat satellite imagery. The process involves five key steps, beginning with the acquisition of data from the Google Earth Engine, where Landsat 8 satellite images with a temporal resolution of 16 days are freely available and for this research were obtained using a monthly median composite approach for the month following the December 2019 fire event. This method enhances the data quality by reducing noise and mitigating the effects of outliers, providing a clearer representation of the affected areas after the wildfire. Despite this relatively low revisit frequency, the high spatial resolution of Landsat 8 images enables detailed capture of forest fire dynamics.

In addition to Landsat-8 data, incorporated the MODIS Burned Area Monthly product for validation purposes. This dataset, with a spatial resolution of approximately 500 m, provides a comprehensive fire footprint that highlights the extent of the burned areas, allowing for a robust comparison with the model's results. Using MODIS data adds an independent layer of validation to assess the performance of our model and ensures that our findings are consistent with widely accepted fire detection methodologies.

To enhance both spatial and temporal resolution, Sentinel-2 imagery was integrated into the methodology. Sentinel-2, with its 5-day revisit cycle and 10–20 m spatial resolution, complements Landsat-8's higher spatial resolution by providing more frequent imagery. This combination addresses the temporal limitations of Landsat-8 while maintaining fine spatial details, enabling more timely detection of wildfires (See Table 1).

2.2.1 Preprocessing and feature extraction

The initial stage of the methodology involves preprocessing the acquired Landsat images to enhance their quality and remove noise. This is achieved through the application of a Gradient Weighting Filter, which reduces noise intensity by replacing it with weighted values from neighbouring pixels. To ensure that important boundaries between burned and unburned areas are preserved, the filter parameters were carefully tuned to minimise the risk of edge blurring. This step was critical for maintaining the clarity of fire perimeters and other key features in the image. While the Gradient Weighting Filter was applied for noise reduction with careful parameter adjustment to preserve edges (Dao et al. 2021), future studies will explore the Bilateral Filter. This filter is noted for its dual emphasis on spatial and intensity differences, providing edge-preserving noise reduction that could further refine the delineation of fire perimeters in wildfire imagery (Nkomba et al. 2023). Subsequently, K-means clustering is employed for segmentation, dividing the image into distinct regions based on cluster centring operations. This segmentation technique aids in isolating areas of interest within the observed image (Siddiqui and Yahya 2022). While K-means clustering provided a straightforward method for unsupervised classification of burned and unburned areas in this study, its limitations in handling complex environments, such as those with clouds and smoke, are acknowledged (Coogan et al. 2022). In such cases, more sophisticated methods, including region-growing algorithms and Object-Based Image Analysis (OBIA), offer a promising alternative (Ez-zahouani et al. 2023).

Table 1 Landsat-8/OLI channels for active fire detection algorithm and primary applications at 30 m resolution (Schroeder et al., 2016)

OLI Channel	Wavelength (µm)	Band Name	Resolution (m)	Application
1	0.43–0.45	Coastal	30	Active fire detection & water mask
2	0.45–0.51	Blue	30	Water mask
3	0.53–0.59	Green	30	Water mask
4	0.64–0.67	Red	30	Water mask
5	0.85–0.88	NIR	30	Active fire detection & water mask
6	1.57–1.65	SWIR 1	30	Active fire detection & water mask
7	2.11–2.29	SWIR 2	30	Active fire detection & water mask

OBIA segments the image into meaningful objects or regions by grouping adjacent pixels with similar spectral characteristics, allowing for better differentiation between fire-affected areas and confounding features like smoke or cloud cover (Labenski 2024). Similarly, region-growing algorithms expand from seed pixels to form larger, coherent regions based on predefined criteria, potentially offering more accurate detection of burned areas in heterogeneous landscapes.

In future research, these techniques will be evaluated against K-means to determine if they provide more robust results in wildfire detection, particularly in challenging environments. This comparative analysis could yield insights into which methods are most effective for large-scale fire monitoring efforts.

Feature extraction is then performed to gather detailed information from the satellite imagery. In addition to extracting spectral features from various bands of Landsat-8, the Normalized Difference Fire Index (NDFI) is computed using Band 7 (SWIR 2) and Band 4 (Red) from Landsat-8. The NDFI is designed to highlight active fire regions by leveraging the spectral properties of these bands, which are sensitive to fire-related changes in the landscape. NDFI plays a crucial role in distinguishing between burned and unburned areas by enhancing the contrast between fire-affected pixels and non-fire regions.

Upon classification of the image, the Euclidean distance between database samples and the query image is calculated, allowing for comparison and identification of differences. This step enables the detection of fire in the forest image by analysing the processed data. The overall methodology is depicted in a block diagram, illustrating the sequential flow of steps involved in the research (Fig. 2).

To improve the accuracy and timeliness of wildfire detection, we propose combining Landsat-8 data with Sentinel-2 imagery. Landsat-8 offers a high spatial resolution of 15–30 m, while Sentinel-2 provides a higher revisit rate of 5 days, allowing for improved real-time fire detection. This combination addresses the temporal limitations of Landsat-8 while maintaining fine spatial details.

In summary, the methodology combines preprocessing, segmentation, feature extraction, classification, and comparison techniques to detect post forest fires conditions in Landsat satellite imagery effectively. By integrating SVM optimisation, the model aims to enhance the accuracy and efficiency of forest fire detection, contributing to improved wildfire management strategies.

2.3 Atmospheric correction

To ensure the accuracy and reliability of the burned area mapping algorithm, it's crucial to correct the top of atmosphere (TOA) reflectance to surface reflectance, particularly in regions (Eck et al. 2003; Kaufman and Tanre 1996). The Land Surface Reflectance Code (LaSRC), initially designed for atmospheric correction of Landsat-8 imagery (Singh and Pandey 2021; Vermote et al. 2016), has been adapted for use with Sentinel-2 A (Doxani et al. 2018; Zhang et al. 2018), offering a suitable solution for this purpose.

Through this research article, we aim to highlight the importance of atmospheric correction in remote sensing studies, particularly in the context of burned area mapping. By leveraging advanced techniques like LaSRC, we contribute to the refinement of methodologies aimed at accurately characterizing and monitoring environmental changes, ultimately facilitating informed decision-making processes for land management and conservation efforts.

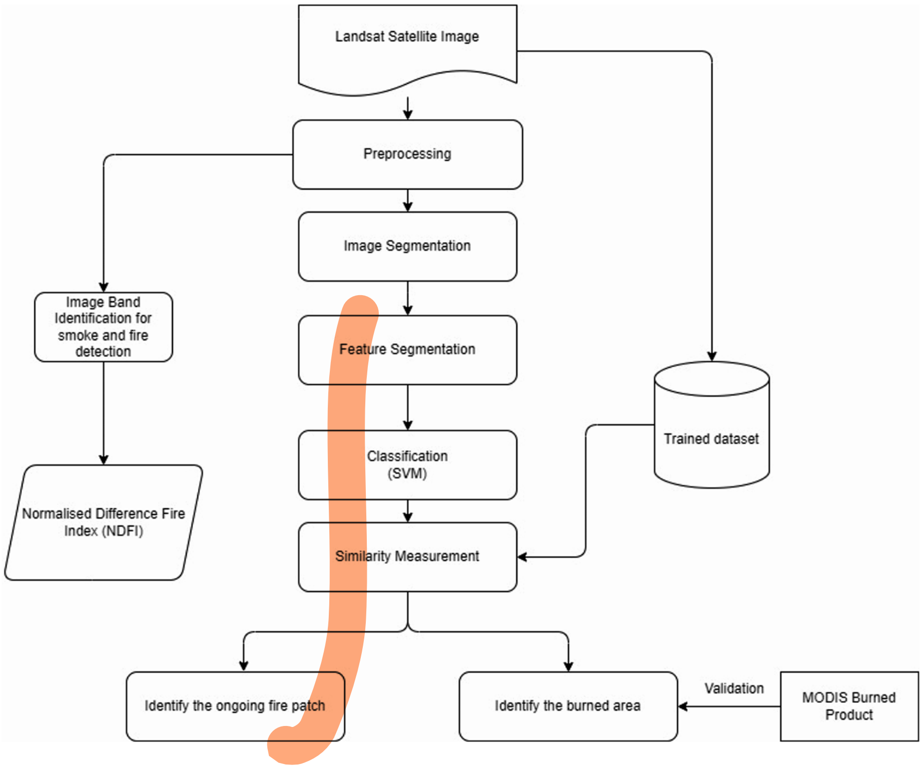

Fig. 2 Overall methodology for this research

2.4 Support vector machine (SVM)

Support Vector Machines (SVMs) have become a prevalent tool in various pattern recognition systems due to their ability to deliver high performance and accurate classification outcomes even with limited training data (Cervantes et al. 2020). The fundamental concept behind SVMs is to construct an optimal hyperplane that effectively separates the input dataset into two classes while maximizing the margin between them (Awad et al. 2015). In our study, SVM is employed to categorize regions of interest as either fire, Burned, or non-fire. The SVM classification function is represented by the following formula:

$$f(x) = \omega \cdot x + b \tag{1}$$

The dividing hyperplane is represented by the function f(x). It aims to maximise the margin between the two nearest vectors by determining the optimal separation. Equation 2 symbolises this optimisation, where x denotes the point on the hyperplane, and b represents the distance from the origin to the point on the hyperplane, known as the hyperplane marginal point.

The objective of SVM is to optimise the margin between two groups, which is achieved by defining two parallel hyperplanes passing through the nearest training samples (Birzhandi et al. 2019). This concept is expressed in Eq. 2, which determines the support vectors along the main separating hyperplane. The optimal point is evaluated based on the magnitude of the weight vector ||w||, aiming to minimise its value.

$$\omega\,\mathrm{x} + \mathrm{b} = \pm\,1 \tag{2}$$

However, a restriction is expressed in Equation Eq. 3 in the attempt to optimise the margin between the hyperplane and the nearest samples:

$$\min\left(\frac{1}{2}\right)\|\,\omega\,\|^2 + C\sum\,{}_{i=1}^{l}\epsilon\,{}_i \tag{3}$$

Whereby ϵ_{i} is the degree of slackness that makes any mistake in misclassification, and the parameter of “C” regularisation influences the rate in our sample of misclassification.

3 Result and discussion

In the results section, it is imperative to highlight the fundamental principles of governing smoke and fire detection through different wavelengths. Smoke, being composed of small particulate matter, interacts more prominently with shorter wavelengths of light, making it easier to detect in such conditions. Conversely, active fire emits thermal radiation, which is more effectively captured by sensors operating in longer wavelengths, particularly in the infrared spectrum. This inherent difference underscores the importance of wavelength selection in designing effective detection systems.

The application of the Gradient Weighting Filter successfully reduced atmospheric noise without significantly affecting edge clarity between burned and unburned areas. The filter’s parameters were carefully adjusted to avoid the risk of edge blurring, ensuring that fire boundaries remained sharp. This preserved edge clarity is essential for accurately detecting fire perimeters, especially in regions with complex topography and land cover. Future work will focus on further enhancing edge preservation through the use of advanced edge-preserving filters such as Bilateral Filters. This approach may offer improved boundary accuracy in mapping fire-affected areas, supporting better tracking of fire spread and damage assessment.

Our study demonstrates that leveraging these principles, using Landsat image from December 2019 can enhance the accuracy and efficiency of fire detection methodologies. By employing sensors capable of detecting both short and long wavelengths, we developed comprehensive detection systems capable of identifying both smoke and active fires with greater precision. This multi-spectral approach offers a more robust solution for wildfire monitoring and early warning systems. Furthermore, our findings underscore the significance of adapting detection strategies to environmental conditions, such as the presence of smoke or varying levels of thermal radiation. Overall, understanding the relationship between wavelength and detection sensitivity is paramount for advancing wildfire detection technology and mitigating the risks posed by such events.

3.1 Spectral profile of active fire, smoke and cloud

The spectral profile analysis revealed distinct variations across different bands for active fire, smoke, and cloud (Fig. 3). Notably, Band 4, corresponding to the red band, exhibited the least value among all bands analyzed. Conversely, Band 7, representing the SWIR 2 band with wavelengths ranging between 2.11 and 2.29, showcased significantly higher values compared to other bands (Fig. 3(a)). This observation indicates a unique spectral signature in the SWIR 2 band, suggesting potential implications for further anal-ysis and interpretation.

For smoke, the spectral profile indicated the highest reflectance value in Band 1 (blue band) and the lowest reflectance value in Band 7 (SWIR 2) (Fig. 3(b)). This distinctive pattern highlights the variability of smoke reflectance across the spectral range, which could be crucial for identifying and differentiating smoke from other features.

In the case of clouds, the spectral profile revealed the lowest reflectance values in Bands 1 (blue band) and 7 (SWIR 2), while the highest reflectance value was observed in Band 5 (NIR) (Fig. 3(c)). This unique spectral behaviour in clouds underscores the importance of the NIR band in detecting cloud features and their properties.

These observations suggest that further investigation into the specific characteristics of these spectral profiles could yield valuable insights for targeted applications and decision-making processes in environmental monitoring and remote sensing.

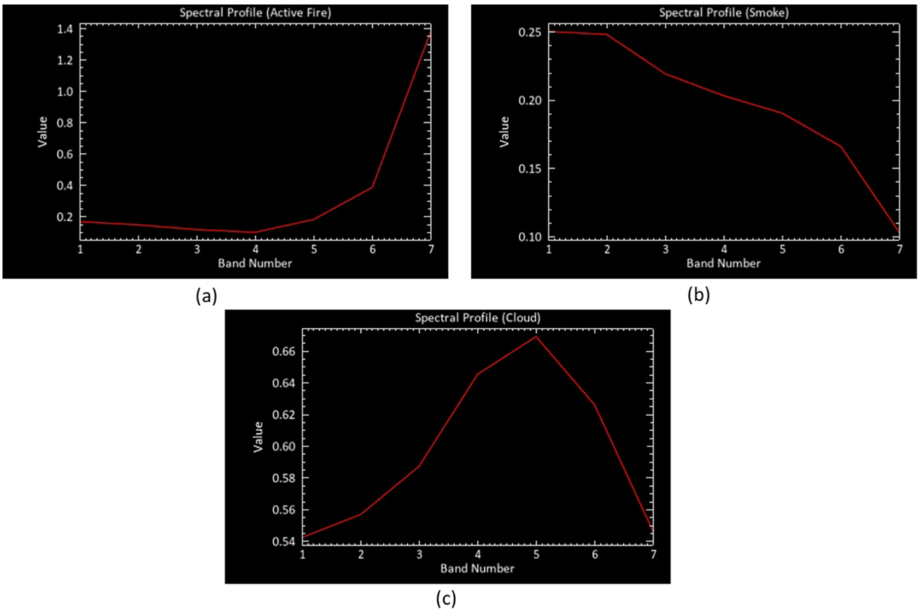

Fig. 3 Spectral profile analysis of different features from Landsat-8 imagery acquired in December 2019 specifically: (**a**) Active Fire: The spectral profile shows the lowest reflectance value in Band 4 (red band) and the highest reflectance value in Band 7 (SWIR 2; wavelengths between 2.11 to 2.29 micrometers). (**b**) Smoke: The spectral profile indicates the highest reflectance value in Band 1 (blue band) and the lowest reflectance value in Band 7 (SWIR 2). (**c**) Cloud: The spectral profile reveals the lowest reflectance values in Bands 1 (blue band) and 7 (SWIR 2), with the highest reflectance value in Band 5 (NIR)

3.2 Active fire comparison across bands

The comparison of active fire activity across different bands of the Landsat 8 image revealed distinctive characteristics. Bands 1 to 5 displayed indications of smoke associated with fire events. Particularly, Band 1 captured the coastal band exhibited high levels of smoke, indicating active fire presence in those regions (Fig. 4).

In Bands 6 and 7, corresponding to the SWIR bands, regions with active fires appeared brighter, indicating intense thermal activity. The SWIR bands, especially Band 7, provided a clear delineation of active fire regions, enhancing detection capabilities.

Interestingly, Band 4 and 5, the Red and NIR bands, showed less smoke compared to Bands 1 to 5 but exhibited high-intensity fire smoke, suggesting its potential utility in identifying areas of intense burning.

These findings underscore the importance of utilising multiple spectral bands for comprehensive fire detection and monitoring, with each band providing unique insights into different aspects of fire behaviour and activity.

3.3 Band for smoke detection

In our investigation of automated wildfire detection using Landsat 8 data, we explored various band combinations to effectively identify smoke, a crucial indicator of wildfire activity. One of the band combinations we examined was utilising Band 1, known as the Coastal Aerosol band. Band 1 (Coastal Aerosol) in Landsat 8 imagery captures wavelengths ranging from 0.43 to 0.45 µm, primarily sensitive to aerosols in the atmosphere. This band is par-

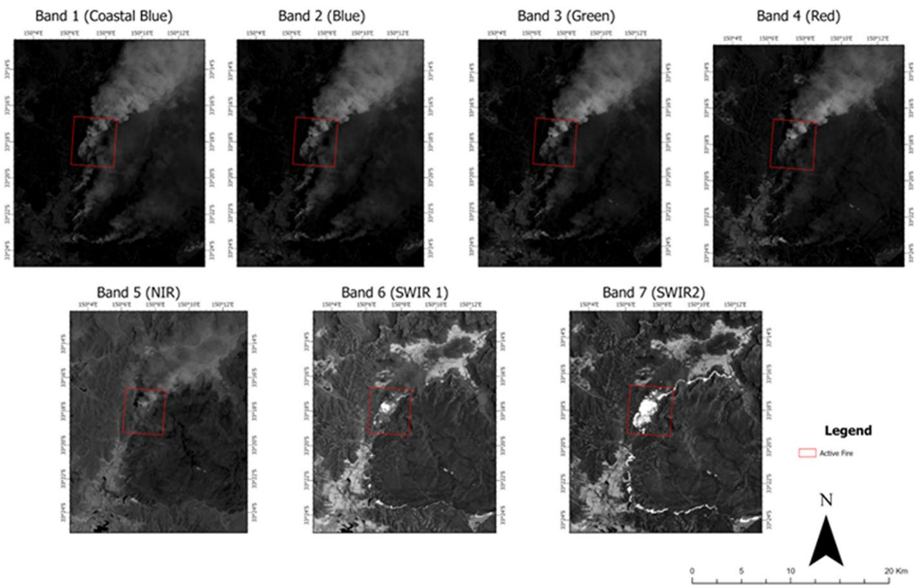

Fig. 4 Comparison of Active Fire Detection Across Landsat 8 Bands: Analysis reveals varying levels of smoke and intensity of fire activity across different spectral bands. Bands 1 to 5 show smoke associated with fires, while Bands 6 and 7 highlight regions of intense thermal activity. Band 5 (NIR) exhibits high-intensity fire smoke, whereas Band 1 (Coastal) detects high smoke concentrations of active fires

ticularly useful for detecting smoke particles due to its sensitivity to fine particulate matter characteristic of smoke plumes.

By analysing satellite imagery of Landsat 8 utilising Band 1, we observed distinct characteristics of smoke that distinguish it from other features in the landscape. Smoke appears as hazy, diffuse patches with varying degrees of opacity, often contrasting sharply with the surrounding terrain (Fig. 5). This distinct appearance aids in the identification and delineation of smoke plumes amidst other environmental elements.

The empirical results obtained from our investigation demonstrate the efficacy of utilising Band 1 in Landsat 8 imagery for smoke detection. The combination of spectral sensitivity to aerosols and spatial resolution offered by Landsat 8 enables the reliable identification of smoke plumes, facilitating prompt wildfire detection and response efforts.

In conclusion, the integration of Band 1 into our analysis framework enhances the capability to detect and monitor wildfire smoke, contributing to the development of more effective automated wildfire detection systems leveraging satellite imagery and machine learning techniques.

3.4 Band combination for active fire

In this empirical investigation of automated wildfire detection using Landsat 8 satellite imagery, we explored various band combinations to effectively identify active fires, which is crucial for timely intervention and mitigation efforts. One of the combinations we examined involved the utilisation of Bands 7, 6, and 5, which correspond to the Shortwave Infrared (SWIR) and Near-Infrared (NIR) spectral regions.

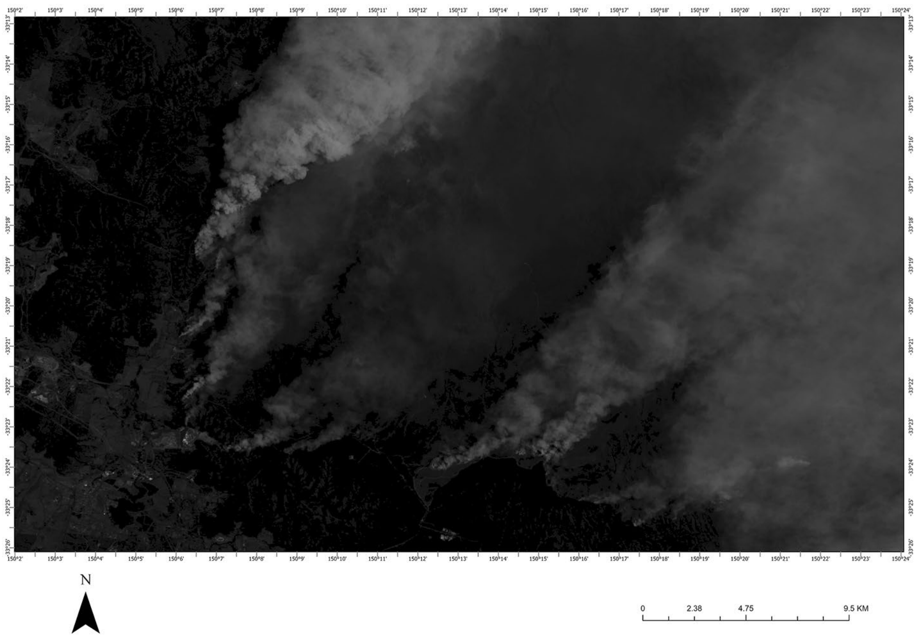

Fig. 5 Landsat 8 imagery showing the effectiveness of Band 1 (Coastal Aerosol) for smoke detection in Australian wildfire regions

Bands 7 and 6 (SWIR) in Landsat 8 imagery capture wavelengths ranging from 2.11 to 2.29 µm and 1.56 to 1.65 µm, respectively. SWIR bands are sensitive to the heat emitted by active fires and can penetrate smoke and atmospheric interference, allowing for the detection of thermal anomalies associated with burning vegetation.

Band 5 (NIR), with wavelengths ranging from 0.85 to 0.88 µm, is particularly useful for distinguishing between burned and unburned areas. Vegetation reflects strongly in the NIR spectrum, but once vegetation is burned, its reflectance decreases significantly. This decrease in NIR reflectance following a fire can be indicative of active burning.

By combining Bands 7, 6, and 5, we can effectively isolate active fire pixels from the surrounding landscape. Analysing the resulting imagery, we can identify clusters of pixels exhibiting high SWIR reflectance (indicative of heat) along with reduced NIR reflectance (indicative of burned vegetation), characteristic of active fire hotspots.

The empirical findings from our investigation demonstrate the efficacy of this band combination for detecting active fires in Australian wildfire-prone regions. Leveraging Landsat 8 data and the specific spectral properties of Bands 7, 6, and 5 enables the development of robust automated wildfire detection systems capable of promptly identifying and monitoring fire activity (Fig. 6).

In conclusion, the integration of Bands 7, 6, and 5 into our analysis framework enhances the capability to detect active fires, facilitating early intervention and mitigation efforts in response to Australian wildfires.

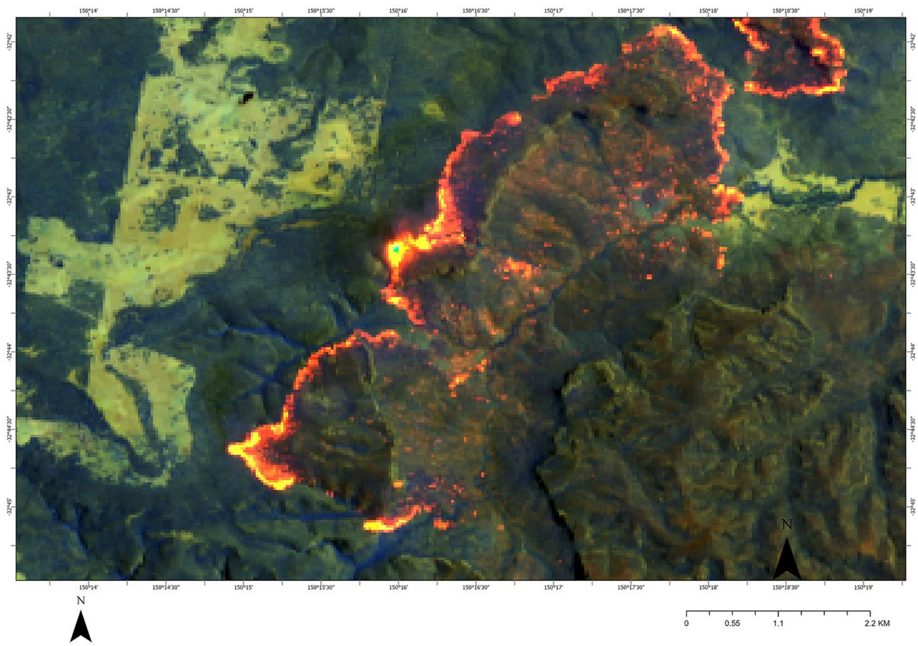

Fig. 6 Landsat 8 imagery highlighting active fire detection through band combination of SWIR (Bands 7 and 6) and NIR (Band 5), aiding in timely wildfire intervention and mitigation strategies in Australian regions

3.5 Support vector algorithm (SVM) algorithm for active and burned area classification

In this section, we present the results of our empirical investigation into the efficacy and potential applications of Support Vector Machine (SVM)-based wildfire detection systems within the context of Australian wildfires, specifically focusing on the Wogan Valley area. We utilised LandSAT 8 imagery from the year 2019 to conduct our analysis.

The active fire detection algorithm for Landsat-8 comprises from the SWIR channel 7, which is sensitive to fires, leveraging the emissive characteristics of fires within the 2.2 µm spectral range. In daytime orbits, the emissive aspect of fire blends with the background, primarily consisting of reflected solar radiation. To distinguish between them, we utilise NIR band 5 data, which exhibit minimal sensitivity to fire-affected pixels but maintain a strong correlation with SWIR channel data over areas without fires (Giglio et al. 2008). During nighttime orbits, the absence of the reflected solar component in the scene enhances the responsiveness of the SWIR band to the emitted radiance from active fires against a subdued background. In both day and nighttime datasets, the radiometric characteristics of active fires generate a SWIR radiance or reflectance anomaly relative to the background, resembling the principle of thermal anomaly detection using mid-to-thermal infrared channels.

The integration of machine learning algorithms, particularly Support Vector Machines (SVMs), with satellite imagery has revolutionised wildfire detection and management strategies. In the context of the Wogan Valley region in 2019, the application of SVMs to Landsat 8 imagery facilitated the extraction of two primary classes: Active Fire and Burned Area (Fig. 7). This approach provided valuable insights into the spatial extent and dynamics of wildfires, enabling timely intervention and informed decision-making by stakeholders.

The SVM-based wildfire detection system proved highly effective in identifying areas with active fire signatures. By analysing thermal anomalies and smoke plumes captured in Landsat 8 imagery, the algorithm accurately delineated regions experiencing ongoing

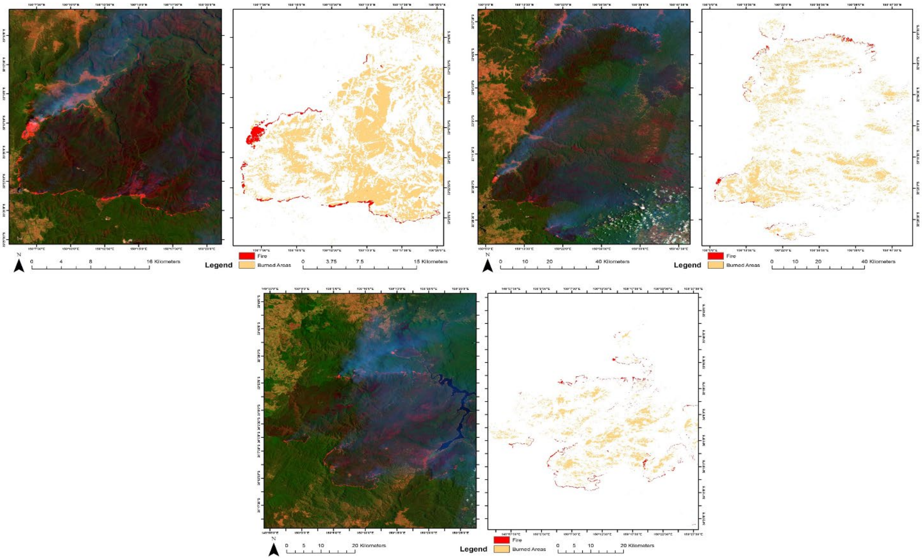

Fig. 7 Classified map obtained from SVM model

wildfire activity. This capability was instrumental in early detection and monitoring, allowing emergency responders to mobilise resources efficiently and mitigate potential risks to human lives and natural ecosystems.

Furthermore, the SVM algorithm demonstrated proficiency in mapping the spatial distribution of burned areas resulting from wildfire events. By detecting spectral changes and patterns associated with fire-induced vegetation damage, the classification process provided detailed insights into the extent of ecological impacts. This information is crucial for assessing post-fire conditions, estimating habitat loss, and prioritising restoration ef-forts to promote ecosystem resilience.

The spatial visualisation of classified outputs allowed for intuitive interpretation and analysis of wildfire dynamics within the study area. Overlaying the classified maps onto high-resolution base maps facilitated the identification of critical areas at risk, enabling stakeholders to prioritise resource allocation and implement targeted mitigation measures. Moreover, temporal analysis of Landsat imagery captured before, during, and after wildfire events provided insights into the temporal evolution of fire activity, including patterns of fire spread and post-fire vegetation recovery.

In summary, the integration of SVMs with Landsat 8 imagery holds significant promise for enhancing wildfire monitoring and management efforts in fire-prone regions such as the Wogan Valley. By leveraging machine learning algorithms to analyse satellite data, stakeholders can gain actionable insights into wildfire dynamics, enabling proactive decision-making and effective response strategies. Moving forward, continued research and refinement of machine learning techniques, coupled with advances in remote sensing technologies, will further enhance the efficacy and scalability of wildfire detection systems, contributing to the resilience and sustainability of ecosystems affected by wildfires.

To validate the accuracy of the burned areas detected by the SVM model, we utilised the MODIS Burned Area Monthly product. Figure 8 presents the observed burned areas as identified by the MODIS Burned Area data. The MODIS dataset provides a comprehensive fire footprint, highlighting the regions affected by the December 2019 wildfire event.

The inclusion of Fig. 8 and 9 alongside the model-detected burned areas (Fig. 7) allows for a direct comparison between the observed fire-affected regions from the satellite-based MODIS product and the areas identified through the SVM model. This visual validation reinforces the findings by illustrating the consistency and accuracy of the model in detecting fire-affected areas in the study region.

3.6 Normalised difference fire index (NDFI)

Innovative approaches in fire index derivation were explored, focusing on leveraging the distinct spectral characteristics of the Short-Wave Infrared 2 (SWIR 2) band and the red band of Landsat 8 imagery (Eq. 4). The spectral profile analysis indicated that active fires exhibit maximum intensity in the SWIR band and minimum intensity in the red band, providing a basis for developing an effective fire index.

The newly proposed Normalized Difference Fire Index (NDFI) utilises Band 7 (SWIR 2) and Band 4 (Red) to delineate active fire regions. The formula for NDFI is calculated as follows:

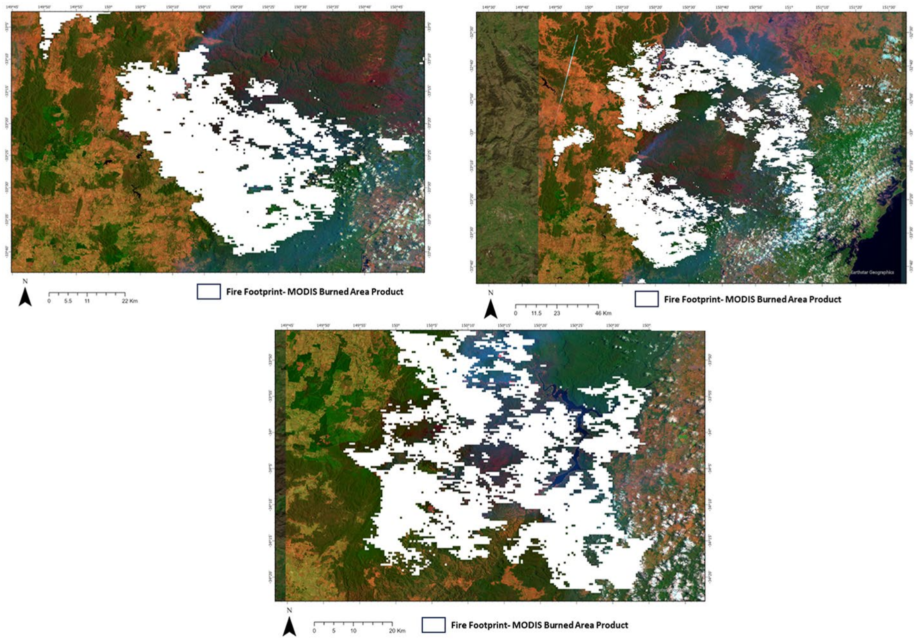

Fig. 8 Observed burned areas derived from MODIS Burned Area Monthly data for December 2019 in Wolgan Valley and surrounding regions, highlighting the fire footprint in the Blue Mountains National Park, Gardens of Stone National Park, and Wollemi National Park

$$\mathrm{NDFI} = \frac{(SWIR2 - Red)}{(SWIR\,2 + Red)} \tag{4}$$

This index capitalises on the spectral properties of active fires, where the reflectance values in the SWIR 2 band are substantially higher compared to the red band (Fig. 8).

3.7 Comparative performance of fire detection methods

The comparison of NDFI, Normalized Burn Ratio (NBR), SVM, and Fire Radiative Power (FRP) in detecting and characterising fires underscores the strengths and limitations of each approach in real-world scenarios. SVM achieved the highest overall accuracy and F1-score, reflecting its robust capability to classify fire and non-fire regions effectively. By enhancing a comprehensive set of input features, SVM excels at adapting to diverse fire conditions but requires extensive training data and computational resources. In contrast, NDFI demonstrated high sensitivity to vegetation changes and smaller fire events, making it well-suited for detailed spatial mapping of burned and unburned areas. Its use of specific spectral bands, such as SWIR2 and Red, enhances fire detection accuracy but is constrained by the moderate temporal resolution of the satellite data.

NBR, derived from near-infrared and shortwave infrared bands, remains a reliable tool for assessing burn severity and post-fire vegetation recovery over broad regions. However, it tends to underperform with smaller or low-intensity fires due to limited spectral sensitivity. FRP, on the other hand, offers near real-time fire monitoring and quantification of fire

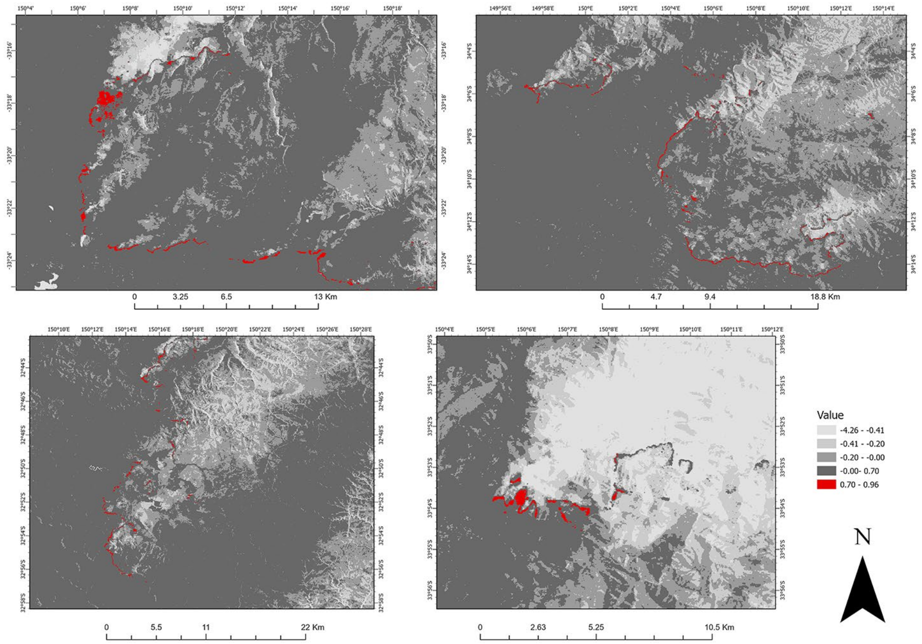

Fig. 9 Landsat 8 imagery depicting active fire regions alongside the image generated using the innovative Fire Index leveraging SWIR and red bands, showcasing improved accuracy in fire detection

radiative energy, providing critical insights into fire intensity and combustion dynamics. While its coarser spatial resolution limits its ability to capture fine-scale fire patterns, FRP is invaluable for rapid assessments of fire activity and energy output. Together, these methods complement one another, demonstrating the need for integrated approaches to enhance fire detection and management strategies across spatial and temporal scales.

The results of this comparison are presented in Table 2, which summarises the performance of the SVM model and NDFI against the ground data from Landsat 8.

3.8 Validation of burned area detection

Figure 10 shows the accuracy of the model's detection of burned areas, validated by comparing the model's results with an official fire-burned boundary shapefile obtained from the NSW National Parks and Wildlife Service (NPWS) Fire History - Wildfires and Prescribed Burns data for the 2019–2020 wildfire season. The NPWS data provides an official boundary of the wildfire that occurred during this period.

The visual comparison between the model's burned area output and the NPWS fire boundary, as illustrated in Fig. 10, demonstrates a strong correlation between the two. The red boundary in the map represents the official fire extent as documented by NPWS, and the model's results closely align with this boundary. This indicates that the model accurately delineated the fire-affected areas. This validation supports the reliability of the model in detecting wildfire boundaries, even in challenging terrain, confirming its potential for effective wildfire monitoring and decision-making in future events.

Table 2 Comparative performance metrics for NDFI, NBR, SVM, and FRP in fire detection and characterization

Metric	SVM	NDFI	NBR	FRP
Precision	0.91	0.89	0.85	0.83
Recall	0.88	0.87	0.83	0.81
F1-Score	0.89	0.88	0.84	0.82
Overall Accuracy	0.92	0.90	0.86	0.84
Detection Sensitivity	High adaptability with training data	High sensitivity to small fires	Effective for burned area mapping	Captures fire intensity
Spatial Resolution	30 m (Landsat)	30 m (Landsat)	30 m (Landsat)	~1 km (MODIS)
Key Strengths	Sensitive to vegetation and topography changes	Widely used for burn severity mapping	Can classify multiple fire conditions	Real-time fire energy monitoring

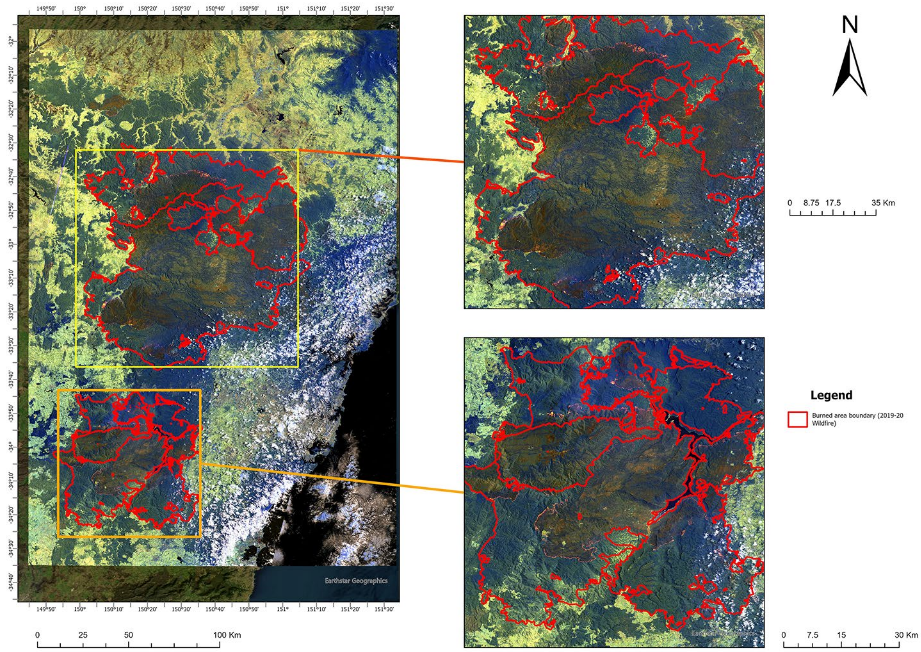

Fig. 10 Comparison of the model-predicted burned areas with the official fire boundary from the NSW National Parks and Wildlife Service (NPWS) Fire History - Wildfires and Prescribed Burns data for the 2019–2020 wildfire season. The red boundary represents the official fire extent, showing strong alignment with the model's detected burned areas, validating the accuracy of the fire detection model

4 Conclusion

For many years, the biomass burning research and data user community has relied on satellite data with coarser spatial resolutions (≥1 km) to map and monitor fire-affected areas. While current operational satellite-based active fire detection systems offer routine global fire activity observations, they lack the spatial detail needed for landscape analyses and tactical fire management.

The increasing availability of high and moderate spatial resolution Earth observation systems, such as Landsat-class instruments, is expected to change this situation. The launch of Landsat-8 in 2013 expanded the network of moderate spatial resolution sensors, and the ongoing development of Landsat-9 could extend this capability into the next decade. Additionally, the adoption of open data policies has boosted the utilisation of Land-sat data across various scientific applications, including biomass burning studies.

The SVM-based wildfire detection system offers several key advantages, including early detection of fire activity, precise mapping of burned areas, and the ability to provide timely information to emergency responders and decision-makers. By leveraging satellite data and machine learning algorithms, stakeholders can gain valuable insights into wildfire dynamics, facilitating proactive measures to mitigate risks and minimise impacts on human lives, infrastructure, and ecosystems.

In addition to the above, the study investigated several aspects related to active fire detection and analysis. Spectral profile analysis revealed significant differences in reflectance values across different spectral bands, with active fires exhibiting maximum intensity in the SWIR band and minimum intensity in the red band. Moreover, comparing active fire detection across bands highlighted the efficacy of utilising SWIR and red bands for improved accuracy.

The study also introduced the Normalised Difference Fire Index (NDFI), an innovative approach to fire index derivation. By leveraging the distinct spectral characteristics of Landsat 8 imagery's SWIR 2 and red bands, NDFI provides a robust method for delineating active fire regions. This index capitalises on the spectral properties of active fires, where reflectance values in the SWIR 2 band are substantially higher compared to the red band.

While MODIS data was used for validation in this study, future research could benefit from integrating Thermal Infrared (TIR) data from sensors like VIIRS or MODIS to improve nighttime fire detection. TIR data is particularly sensitive to thermal emissions, making it ideal for detecting active fires in low-light or nighttime conditions. Combining TIR with SWIR and NIR bands could provide a more robust solution for monitoring fire activity throughout both day and night, offering more accurate and timely fire detection across various conditions.

Despite the progress made, there remain opportunities for further research and development in this field. Continued refinement of machine learning algorithms, integration of additional data sources such as weather data and historical fire records, and advancements in remote sensing technologies will enhance the accuracy, scalability, and utility of wildfire detection systems.

Moreover, efforts should be directed towards addressing challenges such as the availability of high-quality training data, ensuring the reliability and accuracy of satellite imagery, and improving the interpretability of machine learning models. By addressing these challenges, stakeholders can maximise the effectiveness of SVM-based wildfire detection systems and support more informed decision-making in wildfire management.

In summary, the findings of this study highlight the potential of machine learning algorithms, particularly SVMs, to revolutionise wildfire detection and management strategies. By harnessing the power of artificial intelligence and remote sensing technologies, we can enhance our ability to detect wildfires early, mitigate their impacts, and protect both human lives and natural ecosystems in fire-prone regions.

5 Future works

Future works in the field of wildfire detection and management present numerous avenues for research and development to further improve the efficacy and applicability of machine learning-based approaches. One area of focus is the integration of diverse data sources, including high-resolution satellite imagery, weather data, land cover maps, and socio-economic data. By effectively integrating and analysing these multi-dimensional datasets, researchers can gain a more comprehensive understanding of wildfire dynamics, enabling more accurate and proactive wildfire detection and management strategies.

Future research will explore advanced edge-preserving techniques to improve the accuracy of fire perimeter delineation in satellite imagery. In particular, the Bilateral Filter, known for its noise reduction capabilities while preserving sharp edges, shows potential to enhance the clarity of boundaries between burned and unburned areas. Incorporating the Bilateral Filter could support more precise fire perimeter mapping and improve the accuracy of damage assessments and containment strategies. Additionally, combining the Bilateral Filter with other methods, such as Anisotropic Diffusion, may offer even greater edge definition in challenging wildfire scenarios, enabling more accurate post-fire analysis and vegetation recovery studies.

Combining satellite imagery from Landsat-8 and Sentinel-2 is one such avenue that could significantly improve the spatial and temporal resolution of wildfire monitoring systems. While Landsat-8 offers a high spatial resolution of 15–30 m, Sentinel-2's revisit cycle of 5 days enhances temporal frequency, allowing for more continuous monitoring. The integration of these two datasets addresses the trade-offs between spatial detail and real-time monitoring, providing better tools for early fire detection and real-time response coordination. Additionally, comparing these combined datasets to MODIS could provide valuable insights into balancing the trade-offs between temporal frequency and spatial resolution, particularly for detecting both small and large-scale fire events.

Advanced machine learning techniques offer another promising direction for future research. Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have the potential to learn complex spatiotemporal patterns from satellite imagery and other data sources. By further exploring and refining these techniques, researchers can improve the accuracy and efficiency of wildfire detection models, enhancing our ability to predict and respond to wildfire events.

Developing real-time monitoring and prediction systems is also a critical area for future work. By continuously analysing satellite imagery and environmental data streams in real-time, researchers can detect wildfires early and forecast their behaviour more accurately. Integrating machine learning algorithms with real-time data processing framework could facilitate rapid decision-making and response coordination during wildfire emergencies, ultimately saving lives and reducing the impact on ecosystems and infrastructure.

Addressing the challenge of interpretability in machine learning models is another important area for future research. Developing explainable AI techniques that provide insights into model predictions and quantify uncertainties associated with wildfire risk assessments can enhance trust and acceptance of wildfire detection systems among stakeholders. Additionally, efforts to quantify and communicate the uncertainty inherent in wildfire predictions can improve decision-making under uncertainty and support more effective wildfire management strategies.

The integration of unmanned aerial vehicles (UAVs) equipped with sensors for aerial imagery and remote sensing presents another opportunity for future research. UAVs can complement satellite-based monitoring systems, especially in areas with dense vegetation or challenging terrain. By integrating UAV data with machine learning algorithms, researchers can improve localised wildfire detection and response capabilities, enabling more targeted and efficient firefighting efforts. Moreover, adding SWIR sensors on UAVs can enhance real-time monitoring of forests to detect and prevent fires more effectively(Singh et al. 2024; Sos et al. 2023).

In addition to the aforementioned areas of research, the utilisation and further development of the Normalised Difference Fire Index (NDFI) present promising prospects for future work in wildfire detection and management. NDFI, which leverages the spectral characteristics of SWIR and red bands from satellite imagery, offers a robust method for delineating active fire regions. Incorporating NDFI into existing wildfire detection systems can enhance their accuracy and effectiveness, particularly in identifying early-stage fire activity and mapping burned areas with greater precision.

Future research efforts could focus on refining and optimising the NDFI algorithm, exploring its applicability across different geographical regions and environmental conditions, and integrating it into real-time monitoring and prediction systems (Singh et al. 2022a, b). By incorporating NDFI into the toolkit of wildfire detection and management strategies, stakeholders can benefit from enhanced capabilities in early warning, response coordination, and risk mitigation, ultimately leading to improved outcomes in protecting lives and ecosystems from the devastating impacts of wildfires.

Furthermore, involving local communities in wildfire monitoring and management efforts through citizen science initiatives and community-based monitoring programs can enhance data collection and situational awareness. By integrating crowdsourced data with machine learning algorithms, researchers can improve wildfire detection and risk assessment at local scales, empowering communities to take proactive measures to protect themselves and their environment.

Finally, future research should also consider the implications of climate change on wildfire dynamics. With climate change expected to influence wildfire frequency, intensity, and spatial distribution, developing adaptive wildfire detection and management strategies that account for future climate scenarios will be essential for building resilience to wildfire hazards. By leveraging advances in technology, data science, and interdisciplinary collaboration, future research in wildfire detection and management can help mitigate the impacts of wildfires and protect lives and ecosystems.

Acknowledgements We thank the University of the Sunshine Coast, Queensland, Australia, and SmartSat CRC for their generous support for this PhD research. The financial assistance provided by these entities enabled us to pursue our research objectives and complete our work promptly. Without their support, this work would not have been possible.

Author contributions Conceptualization, H.S., and S.S.; methodology, H.S., and S.S.; software, H.S., L.K., S.S.; validation, H.S., L.K., and S.S.; formal analysis, H.S.; investigation, H.S., L.K., and S.S.; resources, H.S., L.K., and S.S.; data curation, H.S., L.K. and S.S.; writing—original draft preparation, H.S., S.S.; writing—review and editing, H.S., L.K. and S.S.; visualization, H.S., L.K., and S.S.; supervision, S.S. and L.K.; project administration, H.S. and S.S.; funding acquisition, S.S. All authors have read and agreed to the published version of the manuscript.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Data availability The data supporting the findings of this study are available upon reasonable request.

Declarations

Ethical approval This research was conducted following ethical guidelines and principles set forth by the University of the Sunshine Coast. All data used in this study were acquired and processed in compliance with relevant ethical standards. The use of satellite data, specifically from LandSAT-8, complied with all applicable guidelines for remote sensing research. The study's methodology aimed to minimise environmental impact and uphold the highest standards of scientific integrity and accuracy. This study did not involve human or animal subjects. Thus, there were no requirements for informed consent or specific ethical considerations related to participant rights and welfare.

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abbass K, Qasim MZ, Song H, Murshed M, Mahmood H, Younis I (2022) A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environ Sci Pollut Res 29:42539–42559. https://doi.org/10.1007/s11356-022-19718-6

Awad M, Khanna R, Awad M, Khanna R (2015) Support vector machines for classification. Efficient learning machines: Theories, concepts, and applications for engineers and system designers 39–66

Ba R, Song W, Lo S, Xie Z (2020) Spectral characteristic analysis of burned area based on MODIS Data, in: The Proceedings of 11th Asia-Oceania Symposium on Fire Science and Technology 11th. Springer, pp. 391–404

Birzhandi P, Kim KT, Lee B, Youn HY (2019) Reduction of training data using parallel hyperplane for support vector machine. Appl Artif Intell 33:497–516

Carling C, Bloomfield J, Nelson L, Reilly T, Carling C, Bloomfield J, Nelsen L, Reilly T (2008) The role of motion analysis in elite soccer: contemporary performance measurements techniques and work rate data. Sports Med.38(10):839–62. Sports Med 38, 839–862

Cervantes J, Garcia-Lamont F, Rodríguez-Mazahua L, Lopez A (2020) A comprehensive survey on support vector machine classification: applications, challenges and trends. Neurocomputing 408:189–215

Chuvieco E, Van der Mouillot F, San Miguel J, Tanase M, Koutsias N, García M, Yebra M, Padilla M, Gitas I (2019) Historical background and current developments for mapping burned area from satellite Earth observation. Remote Sens Environ 225:45–64

Chuvieco E, Yebra M, Martino S, Thonicke K, Gómez-Giménez M, San-Miguel J, Oom D, Velea R, Mouillot F, Molina JR (2023) Towards an integrated approach to wildfire risk assessment: when, where, what and how may the landscapes burn. Fire 6:215

Coogan SCP, Aftergood O, Flannigan MD (2022) Human-and lightning-caused wildland fire ignition clusters in British Columbia, Canada. Int J Wildland Fire 31:1043–1055

Dalezios NR, Kalabokidis K, Koutsias N, Vasilakos C (2017) Wildfires and remote sensing: an overview. Remote Sens Hydrometeorological Hazards 211–236

Dao PD, Mantripragada K, He Y, Qureshi FZ (2021) Improving hyperspectral image segmentation by applying inverse noise weighting and outlier removal for optimal scale selection. ISPRS J Photogrammetry Remote Sens 171:348–366

Dhall A, Dhasade A, Nalwade A, VK MR, Kulkarni V (2020) A survey on systematic approaches in managing forest fires. Appl Geogr 121:102266

Doxani G, Vermote E, Roger J-C, Gascon F, Adriaensen S, Frantz D, Hagolle O, Hollstein A, Kirches G, Li F, Louis J, Mangin A, Pahlevan N, Pflug B, Vanhellemont Q (2018) Remote Sens (Basel) 10:352. https://doi.org/10.3390/rs10020352. Atmospheric Correction Inter-Comparison Exercise

Eck TF, Holben BN, Ward DE, Mukelabai MM, Dubovik O, Smirnov A, Schafer JS, Hsu NC, Piketh SJ, Queface A, Roux J, Le, Swap RJ, Slutsker I (2003) Variability of biomass burning aerosol optical characteristics in southern Africa during the SAFARI 2000 dry season campaign and a comparison of single scattering albedo estimates from radiometric measurements. J Geophys Research: Atmos 108. https://doi.org/10.1029/2002JD002321

Eliott MG, Venn TJ, Lewis T, Farrar M, Srivastava SK (2021) A prescribed fire cost model for public lands in south-east Queensland. Policy Econ 132:102579. https://doi.org/10.1016/j.forpol.2021.102579

Ez-zahouani B, Kharki EL, Kanga O, Idé S, Zouiten M (2023) Determination of segmentation parameters for object-based remote sensing image analysis from conventional to recent approaches: a review. Int J Geoinformatics 19

Fujioka T, Chappell J (2010) History of Australian aridity: chronology in the evolution of arid landscapes. Geol Soc Lond Special Publications 346:121–139

Garcia CA, Savilaakso S, Verburg RW, Gutierrez V, Wilson SJ, Krug CB, Sassen M, Robinson BE, Moersberger H, Naimi B, Rhemtulla JM, Dessard H, Gond V, Vermeulen C, Trolliet F, Oszwald J, Quétier F, Pietsch SA, Bastin J-F, Dray A, Araújo MB, Ghazoul J, Waeber PO (2020) The Global Forest Transition as a Human Affair. One Earth 2:417–428. https://doi.org/10.1016/j.oneear.2020.05.002

Giglio L, Csiszar I, Restás Á, Morisette JT, Schroeder W, Morton D, Justice CO (2008) Active fire detection and characterization with the advanced spaceborne thermal emission and reflection radiometer (ASTER). Remote Sens Environ 112:3055–3063. https://doi.org/10.1016/j.rse.2008.03.003

Guth PL, Craven T, Chester T, O'Leary Z, Shotwell J (2005) Fire location from a single osborne firefinder and a dem, in: ASPRS 2005 Annual Conference Geospatial Goes Global: From Your Neighborhood to the Whole Planet

Jain P, Coogan SCP, Subramanian SG, Crowley M, Taylor S, Flannigan MD (2020) A review of machine learning applications in wildfire science and management. Environ Reviews 28:478–505. https://doi.org/10.1139/er-2020-0019

Kar A, Nath N, Kemprai U (2024) Performance analysis of support Vector Machine (SVM) on challenging datasets for Forest Fire Detection. arXiv preprint arXiv:2401.12924.

Kaufman YJ, Tanre D (1996) Strategy for direct and indirect methods for correcting the aerosol effect on remote sensing: from AVHRR to EOS-MODIS. Remote Sens Environ 55:65–79

Krogh M, Gorissen S, Baird IRC, Keith DA (2022) Impacts of the Gospers Mountain Wildfire on the flora and fauna of mining-impacted Newnes Plateau Shrub Swamps in Australia's Eastern Highlands. Australian Zoologist 42:199–216. https://doi.org/10.7882/AZ.2022.023

Kyrkou C, Kolios P, Theocharides T, Polycarpou M (2022) Machine learning for emergency management: a survey and future outlook. Proc IEEE 111:19–41

Labenski P (2024) Assessing fuels in European temperate forests and heathlands using remote sensing

McCarthy NF, Tohidi A, Aziz Y, Dennie M, Valero MM, Hu N (2021) A deep learning approach to downscale geostationary satellite imagery for decision support in high impact wildfires. Forests 12:294

Mohapatra A, Trinh T (2022) Early wildfire detection technologies in practice—a review. Sustainability 14:12270

Nkomba FE, Kombe T, Ele P (2023) Automatic urban boundary delineation in equatorial regions using SAR imagery: a comprehensive approach with decomposition, morphology, and statistical active contours. Int J Adv Comput Res 13:62

Pérez-Sánchez J, Senent-Aparicio J, Díaz-Palmero JM, de Dios Cabezas-Cerezo J (2017) A comparative study of fire weather indices in a semiarid south-eastern Europe region. Case of study: Murcia (Spain). Sci Total Environ 590:761–774

Siddiqui FU, Yahya A (2022) Clustering techniques for image segmentation. Springer

Singh H, Pandey AC (2021) Land deformation monitoring using optical remote sensing and PS-InSAR technique nearby Gangotri glacier in higher Himalayas. Model Earth Syst Environ 7:221–233. https://doi.org/10.1007/s40808-020-00889-5

Singh H, Meraj G, Singh S, Shrivastava V, Sharma V, Farooq M, Kanga S, Singh SK, Kumar P (2022a) Status of Air Pollution during COVID-19-Induced Lockdown in Delhi, India. Atmos (Basel) 13:2090. https://doi.org/10.3390/atmos13122090

Singh S, Singh H, Sharma V, Shrivastava V, Kumar P, Kanga S, Sahu N, Meraj G, Farooq M, Singh SK (2022b) Impact of forest fires on air quality in wolgan valley, new south wales, australia—a mapping and monitoring study using Google earth engine. Forests 13. https://doi.org/10.3390/f13010004

Singh H, Ang L-M, Lewis T, Paudyal D, Acuna M, Srivastava PK, Srivastava SK (2024) Trending and emerging prospects of physics-based and ML-based wildfire spread models: a comprehensive review. J Res (Harbin) 35:135. https://doi.org/10.1007/s11676-024-01783-x

Sos J, Penglase K, Lewis T, Srivastava PK, Singh H, Srivastava SK (2023) Mapping and monitoring of vegetation regeneration and fuel under major transmission power lines through image and photogrammetric analysis of drone-derived data. Geocarto Int 38. https://doi.org/10.1080/10106049.2023.2280597

Srivastava SK, King L, Mitchell C, Wiegand A, Carter RW, Shapcott A, Russell-Smith J (2013) Ecological implications of standard fire-mapping approaches for fire management of the World Heritage Area, Fraser Island, Australia. Int J Wildland Fire 22:381. https://doi.org/10.1071/WF11037

Thompson MP, Wei Y, Calkin DE, O'Connor CD, Dunn CJ, Anderson NM, Hogland JS (2019) Risk management and analytics in wildfire response. Curr Forestry Rep 5:226–239

Varsha VR, Naganandini S, Hariharan C (2024) Utilizing AI and Machine Learning for Natural Disaster Management: Predicting Natural Disasters With AI and Machine Learning, in: Internet of Things and AI for Natural Disaster Management and Prediction. IGI Global, pp. 279–304

Vermote E, Justice C, Claverie M, Franch B (2016) Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sens Environ 185:46–56. https://doi.org/10.1016/j.rse.2016.04.008

Wang J, Roudini S, Hyer EJ, Xu X, Zhou M, Garcia LC, Reid JS, Peterson DA, Da Silva AM (2020) Detecting nighttime fire combustion phase by hybrid application of visible and infrared radiation from Suomi NPP VIIRS. Remote Sens Environ 237:111466

Zhang HK, Roy DP, Yan L, Li Z, Huang H, Vermote E, Skakun S, Roger J-C (2018) Characterization of Sentinel-2A and Landsat-8 top of atmosphere, surface, and nadir BRDF adjusted reflectance and NDVI differences. Remote Sens Environ 215:482–494. https://doi.org/10.1016/j.rse.2018.04.031

Authors and Affiliations

Harikesh Singh[1,2] · Li-Minn Ang[1] · Sanjeev Kumar Srivastava[1]

✉ Harikesh Singh
Harikesh@research.usc.edu.au

[1] School of Science Engineering and Technology, University of the Sunshine Coast, QLD, Australia

[2] SmartSat Cooperative Research Centre, North Terrace, Adelaide, SA 5000, Australia