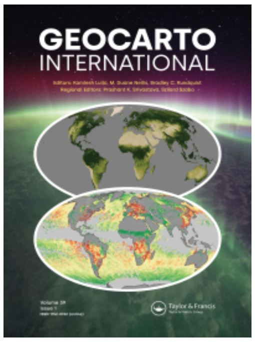

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Identification of forest fire-prone region in Lamington National Park using GIS-based multicriteria technique: validation using field and Sentinel-2-based observations

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ABSTRACT

Lamington National Park in Queensland, Australia, is increasingly threatened by wildfires, intensified by climate change. This study integrates remote sensing, GIS, and the Analytical Hierarchy Process (AHP) to identify fire-prone areas within the park. Eight parameters were analyzed, with major fuel type being the most significant. Multispectral satellite data provided essential insights into landscape changes and vegetation stress, enhancing the understanding of wildfire risks. Historical records, field observations, and remote sensing data were utilized to develop and validate a Forest Fire Risk Index map, highlighting heightened fire susceptibility in the northern and eastern regions due to subtropical humid conditions. The findings emphasise the importance of advanced spatial analysis for proactive wildfire management. Combining remote sensing with GIS and multicriteria decision-making equips conservationists and policymakers with critical tools to strengthen wildfire response strategies, safeguard vital ecosystems, and protect surrounding communities. This approach is valuable for managing similar landscapes globally.

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Forest fire; AHP; forest fire risk index; remote sensing; time since burn

1. Introduction

Australian ecosystems are characterised by vast and diverse forested landscapes, encompassing a rich tapestry of ecosystems that are crucial to the region's ecological balance and overall well-being (DES 2020; Singh and Srivastava 2024). However, these ecosystems face significant challenges, ranging from natural catastrophic events to human-induced disturbances (Singh, Singh, et al. 2022; Kumar et al. 2024). In Queensland, wildfires are becoming more frequent and severe due to climate change, which leads to extended periods of dryness, increasing wildfire likelihood and making them harder to control (Williams et al. 2017; Grantham et al. 2020). On the other hand, intensified rainfall events

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can cause flooding, further endangering communities and ecosystems (Russell-Smith et al. 2003). Therefore, there is a pressing need for robust wildfire management strategies to mitigate these risks.

The constant threat of wildfires in Queensland highlights the importance of creating strong and proactive plans to evaluate the risk of wildfires and put in place successful management techniques. In this regard, Lamington National Park stands out as a significant area for examination and action due to its distinct mix of geography, climate, and ecology. Located in southeastern Queensland, this national park is famous for its rich variety of ecosystems and is also notable for being susceptible to forest fires, which can have significant consequences extending well beyond its boundaries (Hines et al. 2020; Ross et al. 2023).

To address the increasing risk of wildfires in this area, there's a pressing requirement for sophisticated techniques and approaches that can precisely forecast and delineate areas susceptible to wildfires (Tehrany et al. 2019). These efforts are crucial for facilitating proactive actions such as allocating resources, developing mitigation strategies, and protecting both human communities and natural habitats (Singh, Meraj, et al. 2022; Pandey et al. 2023). In the context of big geospatial data analytics, Geographic Information Systems (GIS) play a pivotal role in processing, analysing, and visualising vast amounts of geospatial data to derive meaningful insights (Harikesh et al. 2020; Singh and Pandey 2021). GIS allows for the integration of various data sources, including satellite imagery, sensor data, and field observations, enabling researchers to gain a comprehensive understanding of environmental phenomena like wildfires, Air pollution (Singh, Meraj, et al. 2022). In essence, GIS serves as a fundamental component of big geospatial data analytics, enabling researchers to harness the power of large and diverse datasets to address complex environmental challenges such as wildfire susceptibility (Sos et al. 2023).

Traditionally, wildfire susceptibility mapping relied on historical data, static land-use classifications, and rudimentary statistical models, a methodology constrained by its inability to capture the dynamism of susceptibility, especially in regions undergoing rapid environmental change (Weinstein and Woodbury 2010; Singh et al. 2024). As a result, the field of wildfire susceptibility mapping has undergone a profound transformation. In contrast to data-extensive and high computation time modelling approaches, remote sensing (RS) and geospatial analysis have emerged as invaluable tools for assessing forest fire behaviour (Thompson et al. 2015; Çoban and Erdin 2020; Nuthammachot and Stratoulias 2021; Quan et al. 2021; Singh, Singh, et al. 2022). These techniques offer a distinct advantage in terms of efficiency and reliability, even in remote locations characterised by harsh climatic conditions and vast areas affected by forest fires. Remote sensing technology offers distinct advantages in terms of spatial, spectral, radiometric, and temporal data availability compared to traditional techniques, making it a valuable tool for assessing forest fires (Banskota et al. 2014; Singh, Singh, et al. 2022). With the introduction of advanced sensors, platforms, and implementation methods, it becomes increasingly effective in evaluating the variability and extent of forest fires (Hua and Shao 2017). So far, numerous studies have been conducted to map forest fires in different countries, including but not limited to Australia (Srivastava et al. 2013, 2021; Parker et al. 2015; Eliott et al. 2020; Singh, Singh, et al. 2022; Penglase et al. 2023; Ross et al. 2023), Canada (Xiao-rui et al. 2005; Hall et al. 2020; Woolford et al. 2021; Risk and James 2022), the United States (Akinola and Adegoke 2019; Mohajane et al. 2021; Moris et al. 2022; Truong et al. 2023), Brazil (Mota et al. 2019; Ziccardi et al. 2020; Santana Neto et al. 2023), Russia (Shikhov et al. 2019; Glushkov et al. 2021; Li et al. 2022), and several European nations (Varela et al. 2019; Efthimiou et al. 2020; Müller et al. 2020).

Multicriteria Decision-Making (MCDM) methods like Analytical Hierarchy Process (AHP) (Kumari and Pandey 2020; Lamat et al. 2021; Nasiri et al. 2022; Sivrikaya and Küçük 2022), Fuzzy AHP (Eskandari 2017; Güngöroğlu 2017; Roshani et al. 2023), Analytical Network Process (Hung 2011; Abedi Gheshlaghi et al. 2020), Ordered Weighted Averaging (Valente and Vettorazzi 2008; Xiao et al. 2017; Faramarzi et al. 2021), VIKOR (Sari 2021; Ma et al. 2022; Saner et al. 2022; Biswas et al. 2023), and Technique for the Order of Preference by Similarity to Ideal Solution (TOPSIS) (Sari 2021; Abedi 2022; Ju et al. 2022; Ma et al. 2022; Biswas et al. 2023) have emerged as vital tools. Statistical models, including logistic regression (Milanović et al. 2020), evidential belief functions (Pourghasemi 2016; Nami et al. 2018), and the frequency ratio method (Arca et al. 2020; de Santana et al. 2021), have been used to generate these crucial maps. Yet, the most transformative leap has been the adoption of machine learning (ML) and deep learning-based algorithms for forest fire susceptibility mapping (Kalantar et al. 2020; Achu et al. 2021; Mohajane et al. 2021; Shahfahad et al. 2022; Akıncı and Akıncı 2023; Rihan et al. 2023).

The morphometric factors of the landscape play a fundamental role in mapping forest fire-prone areas (Bajocco et al. 2010). To successfully identify potential forest fire risks within a region, it's imperative to understand all the environmental processes at play. Static physical characteristics such as vegetation type, topography, vegetation density, and drainage, along with dynamic properties like real-time moisture levels, collectively indicate the potential for forest fires resulting from factors like prolonged drought and lightning strikes. The considered variables related to topography, vegetation type, wetness index and the prevailing moisture conditions in the study area, directly influence the susceptibility of an area to forest fires. Moreover, the terrain's topographical features, particularly the digital elevation model (DEM), are of utmost importance for forest fire mapping. These factors enable the extraction of slope, aspect, and wetness characteristics, with the scale and precision of these topographic data directly impacting the accuracy of forest fire susceptibility analyses.

The factors contributing to forest fires require a multi-criteria decision-making approach within a GIS framework. One of the techniques for evaluating the relative significance of these factors is the Analytical Hierarchy Process (AHP), introduced by Saaty (1980). AHP employs a multi-level hierarchical structure involving criteria, sub-criteria, objectives, and alternatives to address intricate decision-making problems and has found application in various domains. Triantaphyllou and Mann (1995) highlighted the significance of AHP in numerous engineering contexts. Tiwari et al. (2021) utilised AHP to assess potential zones prone to forest fires in the Pauri Garhwal region, India. Unver and Ergenc (2021) applied AHP to prioritise forest logging activities, while Feng et al. (2016) integrated AHP for assessing forest resource quality at a regional scale.

Comparatively, fuzzy logic modelling has emerged as an alternative for handling uncertainty and imprecise input data in multi-criteria decision-making. Feizizadeh et al. (2014) demonstrated the effectiveness of fuzzy logic in wildfire risk mapping, particularly in regions with high variability in data accuracy. Similarly, Pourghasemi et al. (2012) applied fuzzy-AHP techniques to landslide susceptibility mapping, showcasing its flexibility in addressing data uncertainties. While fuzzy logic excels in managing uncertainties, AHP remains advantageous for its transparency, simplicity, and effective integration with GIS frameworks. These studies collectively demonstrate the versatility and applicability of AHP and provide a basis for selecting AHP in this study, given the reliable datasets and well-defined criteria specific to Lamington National Park.

Forest fires are a recurring disaster in Lamington National Park, Queensland, Australia, often transpiring annually and exacerbated by the country's seasonal environment (Lowe et al. 2016; Abram et al. 2021). These fires are typically ignited by extensive surface area over short durations and on small spatial scales, coupled with factors like fuel load, climate change, non-native species, forest management practices like fuel accumulation, and economic development, all of which contribute to the increasing vulnerability to fire-related hazards. Table 1 presents a record of recent forest fire incidents in Lamington National Park, Queensland, Australia.

This study uniquely integrates Sentinel-2 remote sensing indices, such as the Enhanced Vegetation Index (EVI) and Topographic Wetness Index (TWI), with field validation to produce a highly accurate fire susceptibility map. Unlike previous studies that rely solely on AHP or machine learning models, this research emphasises the unique characteristics of subtropical ecosystems, which are underrepresented in wildfire susceptibility literature. Specifically, the integration of historical fire data with advanced geospatial analysis targeting Lamington National Park—a biodiverse and ecologically sensitive region—addresses a critical gap in applying remote sensing and GIS-based methods in subtropical environments. Additionally, this approach provides a scalable and interpretable framework for wildfire risk assessment, offering actionable insights for conservation efforts and wildfire management. By combining the interpretability of AHP with the spatial precision of Sentinel-2 indices, this study achieves a balance between methodological rigour and practical application, setting a new benchmark for fire susceptibility mapping in subtropical regions.

Table 1 summarises the key annual statistics of burned area and fire frequency within the study region during the analysis period (2012–2020). This concise version focuses on essential information to provide a clear overview of temporal trends in wildfire activity. The data highlights variations in annual burned areas and the frequency of fire occurrences, which serve as critical inputs for forest fire susceptibility modelling.

For a comprehensive breakdown of the detailed annual and spatial trends, including specific regions affected by wildfires, please refer to the supplementary material (Table S1).

2. Study area and data sets

The study area for this research is Lamington National Park, a biodiverse sanctuary nestled in the southeastern region of Queensland, Australia (Figure 1). Covering approximately 20,590 hectares, Lamington National Park is renowned for its rich ecosystems, housing a diverse array of flora and fauna species. Designated as a UNESCO World Heritage-listed site, the park features subtropical rainforests, eucalypt woodlands, and diverse vegetation types, making it a critical region for biodiversity conservation. However, the park faces escalating threats from wildfires, exacerbated by climate change-induced environmental shifts.

Table 1. Summary of annual wildfire activity in the study area (2012–2020), including total burned area and fire frequency, serving as key inputs for forest fire susceptibility modelling.

Year	Annual fire frequency	Total annual burned area (ha)
2012	1	262.61
2013	2	627.26
2015	2	753.30
2016	3	236.95
2018	2	1837.76
2019	7	5544.601
2021	1	110.96
Total	18	9373.44

Detailed data are available in Supplementary Table S1.

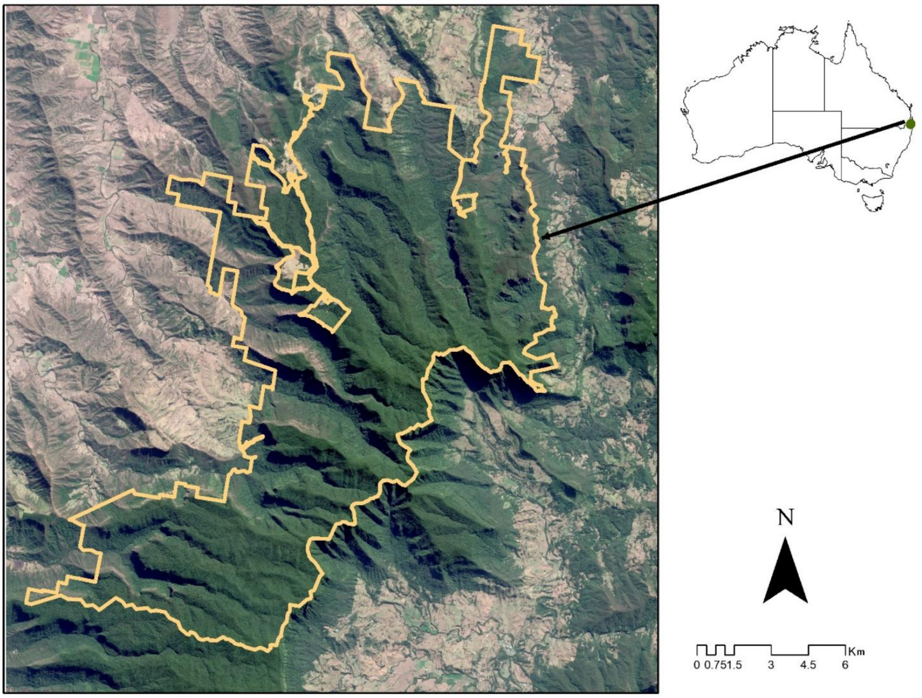

Figure 1. Study area provides a comprehensive overview of the geographical features pertinent to our research. The background image is derived from Sentinel-2 satellite imagery, which vividly displays the actual landscape and characteristics of the study area. This high-resolution image aids in accurately visualising the region, highlighting key elements such as vegetation, water bodies, and terrain variations.

The park experiences a subtropical climate characterised by warm, humid summers and mild, dry winters. Annual rainfall ranges between 1,500 mm and 2,000 mm, with the majority of precipitation occurring between November and March. This seasonal variation significantly influences vegetation moisture levels, contributing to varying degrees of fire susceptibility. Prolonged dry periods and elevated temperatures during summer months increase the likelihood of fire ignition and spread.

Fire history data reveal that the park has experienced several significant wildfire events in the past decade. Notably, the 2019 wildfire season affected over 6,000 hectares, severely impacting vegetation and wildlife. These fires highlight the critical role of climatic factors, such as drought and heatwaves, as well as the importance of understanding topographic influences, including steep slopes and rugged terrain, which exacerbate fire behaviour and pose challenges for firefighting efforts.

To address these challenges, this study employs a robust methodology integrating Geographic Information Systems (GIS) and multicriteria decision-making techniques. Various datasets were utilized, including a Digital Elevation Model (DEM) with a 5-meter resolution, Sentinel-2 imagery for Enhanced Vegetation Index (EVI) and Topographic Wetness Index (TWI) derivation, as well as road, stream, and forest history data sourced from government organizations (Table 2). These datasets were analyzed to assess terrain characteristics, vegetation health, and proximity to water bodies and roads, which are key parameters influencing forest fire susceptibility. This research focuses on understanding fire risk dynamics within Lamington National Park to enhance conservation efforts and mitigate wildfire impacts effectively.

Table 2. Various datasets used in the study.

Data	Resampled resolution	Temporal resolution	Radiometric resolution	Initial data format	Data source and map scale
Digital elevation model (DEM)	5 m	Static		Raster	Geoscience Australia, LiDAR-derived 5 m DEM
Sentinel 2	10 m	5-day revisit	12-bit	Raster	European Space Agency (ESA)
Aspect	5 m	–	–	Raster	Derived from 5 m DEM
Slope	5 m	–	–	Ratser	Derived from 5 m DEM
Topographic wetness type (TWI)	5 m	–	–	Raster	Derived from 5 m DEM
Enhanced vegetative index (EVI)	5 m	–	–	Raster	Sentinel 2 Imagery (Date: 29/07/2023) with 10 m resolution
Regional ecosystem data	5 m	Static	Annual	Raster	Queensland Department of Environment, Science and Innovation, Brisbane (map scale: 1: 1 million)
Road	5 m	Static	–	Vector	Derived from Roads and Tracks data available with the Department of Resources (map-scale of 1:200 K)
Stream	5 m	Static	–	Vector	Derived from drainage network data available with the Department of Resources (map scale 1: 100 000)
Forest fire history data	–	Annual	–	Vector	Queensland Parks and Wildlife Service (2 m accuracy) (The data was utilised as point locations and incorporated into training and testing datasets.)

3. Method

Through the application of the Analytical Hierarchy Process (AHP), this study aimed to identify forest fire-prone regions within Lamington National Park and generate a comprehensive Forest Fire Risk Index (FRI) map. Validation of the FRI map was conducted using field observations and satellite imagery, underscoring the critical role of advanced spatial analytics in bolstering wildfire management strategies and safeguarding vital ecosystems and communities.

The workflow of the present work is shown in Figure 1. The methodology part is divided into 3 sections. At first, different parameters were selected based on case studies with similar characteristics (Feng et al. 2016; Eskandari 2017; Blagojevic et al. 2020; Çoban and Erdin 2020; Nasiri et al. 2022). Fire risk index (FRI) map was generated by implementing AHP on these parameters in a GIS environment. Then, forest fire-prone areas were identified by integrating FFDI and lastly produced results were validated using forest fire report data which was managed by the Queensland government, literature and remote sensing-based index.

3.1. Forest fire risk index generation

A forest fire risk index is a statistical tool designed to depict the magnitude and location of areas at risk of forest fire hazards. It provides insights into the potential severity and spatial distribution of fire-prone areas, aiding in the prioritization of wildfire management strategies to protect life, health, and property. Numerous studies have utilised the Forest Fire Index-based approach to prepare a forest fire map (Kumari and Pandey 2020; Lamat et al. 2021; Sivrikaya and Küçük 2022).

The 9 factors that have a significant influence in mapping fire risk index were identified. The selected factors are Surface slope (S), Aspect (A), Elevation (E), Enhanced vegetation index (EVI), Topographic wetness index (TWI), Major fuel type (MFT), Distance to road (DR), Distance to stream (DS) and Distance to camping site (CS). The AHP model was implemented to estimate the normalised weight (W) of each parameter.

Later, each parameter was classified to five hazard levels defined by its rating score ranging between 2 (for minimum influence) and 10 (for maximum influence). Finally, the fire risk index was calculated using Equation 1.

$$\begin{aligned} \boldsymbol{FRI} = \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} \boldsymbol{W_i} * \boldsymbol{p} &= (\boldsymbol{MFT} * \boldsymbol{W}1) + (\boldsymbol{A} * \boldsymbol{W}2) + (\boldsymbol{S} * \boldsymbol{W}3) + (\boldsymbol{E} * \boldsymbol{W}4) + (\boldsymbol{TWI} * \boldsymbol{W}5) \\ &+ (\boldsymbol{DR} * \boldsymbol{W}6) + (\boldsymbol{DS} * \boldsymbol{W}7) + (\boldsymbol{EVI} * \boldsymbol{W}8) + (\boldsymbol{CS} * \boldsymbol{W}9) \end{aligned}$$

where n = number of parameters, W_i = weight of each parameter, p = parameter used (in terms of rating score).

3.2. Fuel types and fire behaviour potential

Fuel types play a critical role in determining forest fire susceptibility due to variations in their structure, fuel load, and flammability. This study evaluated 14 distinct fuel types based on their fire behaviour potential, which was derived through expert consultation, literature review, and historical fire data. The fire behaviour potential of each fuel type was quantified and weighted using the Analytical Hierarchy Process (AHP). Table 3 presents the 14 fuel types, their respective characteristics, and the assigned weights based on their influence on fire spread and ignition potential.

The weights derived from Table 3 were integrated into the forest fire susceptibility model along with other factors, such as slope, aspect, and TWI. The methodology ensured consistency in the weighting process by adhering to the AHP framework and validating the pairwise comparison matrix (CR < 0.1).

3.3. Analytical hierarchy process

The Analytic Hierarchy Process (AHP) offers an effective approach for addressing intricate multi-criteria decision challenges. It involves breaking down the problem into a hierarchical structure of smaller sub-problems, making them more manageable and allowing for subjective evaluations (Saaty 1980).

The Analytical Hierarchy Process (AHP) was chosen for this study due to its capacity to effectively handle multi-criteria decision-making problems in geospatial contexts. Its interpretability and flexibility allow for the integration of diverse environmental factors, such as vegetation indices and terrain parameters, with field-validated data. AHP remains a robust and widely accepted technique for wildfire susceptibility mapping, particularly in

Table 3. Classification of major fuel types in Lamington National Park, categorised by broad vegetation group (BVG) codes.

BVG code	Broad vegetation group description	Fuel type
11a	Moist to dry open forests to woodlands dominated by *Eucalyptus orgadophila*	Eucalypt
2a	Complex evergreen mesophyll-notophyll vine forest frequently with *Araucaria cunninghamii*	Rainforest
6a	Notophyll vine forest and microphyll fern forest to thicket on high peaks and plateaus of southern Queensland.	Rainforest
8a	Wet tall open forest dominated by species such as *Eucalyptus grandis*	Eucalypt
8b	Moist open forests to tall open forests mostly dominated by *Eucalyptus pilularis*	Eucalypt
13c	Woodlands of *Eucalyptus crebra*	Eucalypt
16c	Woodlands and open woodlands dominated by *Eucalyptus coolabah*	Eucalypt
29b	Open shrublands to open heaths on elevated rocky substrates.	Heath
5a	Araucarian notophyll/microphyll and microphyll vine forests of southern coastal bioregions.	Rainforest
9h	Dry woodlands dominated by species such as *Eucalyptus acmenoides*	Eucalypt
4b	Evergreen to semi-deciduous mesophyll to notophyll vine forest, frequently with *Archontophoenix* spp.	Rainforest
10b	Moist open forests to woodlands dominated by *Corymbia citriodora*	Eucalypt
28e	Low open forest to woodlands dominated by *Lophostemon suaveolens*	Eucalypt
9a	Moist eucalypt open forests to woodlands dominated by a variety of species including *Eucalyptus siderophloia*	Eucalypt

Each BVG description highlights the predominant vegetation type and corresponding fuel type, providing insights into the varying fire behaviours and susceptibilities across the park's diverse ecosystems.

scenarios requiring practical, scalable solutions in complex ecological landscapes like Lamington National Park.

Numerous studies have demonstrated the effectiveness of AHP in wildfire susceptibility and hazard mapping. Tiwari et al. (2021) utilised AHP to map forest fire-prone zones in the Pauri Garhwal region of India, effectively identifying high-risk areas based on multi-criteria evaluation. Similarly, Sivrikaya and Küçük (2022) applied AHP to prioritize forest management activities in Turkey, showcasing its adaptability for multi-criteria problems and its ability to incorporate diverse datasets such as proximity to roads and vegetation health. Çoban et al. (2019) integrated AHP with GIS to produce wildfire hazard maps in Turkey, highlighting its simplicity and interpretability in weighting parameters like slope and vegetation density. Kumari and Pandey (2020) further employed AHP to assess wildfire risks in the Palamau Tiger Reserve in India, demonstrating its reliability in identifying vulnerable areas for targeted wildfire management.

These references validate the utility of AHP as a proven method for forest fire hazard estimation, especially when combined with GIS technologies. By adopting AHP, this study builds upon its established methodologies and extends its application to subtropical ecosystems. The integration of advanced datasets, such as Sentinel-2-derived indices and field validation data, adds further value to this research, providing a novel approach to understanding fire susceptibility in Lamington National Park.

In this research, evaluated the potential significance of various factors related to forest fire susceptibility by assigning scale values ranging from 1 to 9 within a decision matrix. This 9-point scale specifically assesses the non-diagonal relationships among the considered parameters. A value of 1 indicates 'Equal importance', 3 signifies 'Moderate importance', 5 represents 'Significant importance', 7 implies 'Very important' and 9 corresponds to 'Absolutely important'. To derive normalised weights (W), we conducted pair-wise comparisons for each factor, as illustrated in Tables 3 and 4 using a 9×9 matrix shown in Tables 3 and 4.

The Major fuel type and aspect were the factors having the highest normalised weight (28.875 and 18.239), least weight was observed for distance to camping site (2.959).

Table 4. Classification of the parameters and their rating score.

Parameters	Class	Reclassified class	Rating	Weights
Fuel type	11a	1	8	32.65
	2a	2	3	
	6a	3	3	
	8a	4	7	
	8b	5	7	
	13c	6	9	
	16c	7	8	
	29b	8	6	
	5a	9	3	
	9h	10	9	
	4b	11	4	
	10b	12	8	
	28e	13	7	
	9a	14	8	
Aspect	North		2	19.04
	North East		3	
	North West		3	
	East		4	
	Flat		5	
	South East		6	
	West		6	
	South		8	
	South West		10	
Slope (degree)	0–84	0–5	2	12.93
		05–10	3	
		10–15	4	
		15–20	5	
		20–25	6	
		25–30	7	
		30–35	8	
		35–40	9	
		> 45	10	
Elevation (m)	149.118–1189.77	0	2	8.67
		100	3	
		200	4	
		300	5	
		400	6	
		500	7	
		600	8	
		700	9	
		>700	10	
TWI	−0.52–21.66	−0.52	2	7.14
		0	3	
		2	4	
		4	5	
		6	6	
		8	7	
		10	8	
		15	9	
		>15	10	
Distance to road (m)	0–3703.04	> 1000	2	6.19
		1000	3	
		800	4	
		600	5	
		400	6	
		200	7	
		150	8	
		100	9	
		50	10	

(*continued*)

Table 4. Continued.

Parameters	Class	Reclassified class	Rating	Weights
Distance to stream (m)	0–2263.02	50	2	5.84
		100	3	
		150	4	
		200	5	
		250	6	
		500	7	
		1000	8	
		2000	9	
		> 2000	10	
EVI	0.15–1	0.15	10	4.61
		0.2	9	
		0.3	8	
		0.35	7	
		0.4	6	
		0.45	5	
		0.5	4	
		0.7	3	
		> 0.7	2	
Distance from Campsite	0–4563	0–100	1	2.93
		100–200	2	
		200–300	3	
		300–400	4	
		400–500	5	
		500–1000	6	
		1000–2000	7	
		2000–4000	8	
		4000–max	9	

3.3.1. Consistency check

The consistency of the created decision matrix (Section 3.2) was evaluated using the following index:

$$CR = \frac{CI}{RI}$$

where CR is the consistency ratio; CI is the consistency index; RI is the random index.

The acceptable CR must be <0.1. The values of RI are tabulated in Table 5 (Lane and Verdini 1989; Alonso and Lamata 2006). The RI value depends upon the number of factors (n) used in the AHP. Thus, for 9 factors, RI comes out to be 1.45.

CI is calculated using the equation:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

where λ_{max} is the maximum eigenvalue of the comparison matrix, and n is the number of factors.

After analysing Table S2, the value of λ_{max} comes out to be 9.69 and CI is computed to be 0.09. Eventually, using the CR equation, the calculated Consistency ratio is 0.06; this proves that the weights are consistent.

Table 5. Distribution of the forest fire risk zone.

Fire risk zone	Percentage (%)
Low risk	66.3
Moderate risk	29.36
High	4.32

After assessing the consistency of decision matrix, all parameters were reclassified into 5 hazard levels viz. very high, high, moderate, low and very low (more details are in Section 4). The rating score was given for each risk level (Table 4) ranging between 2 and 10.

3.4. Forest fire-prone areas mapping and validation

The FRI map obtained by implementing the AHP model was masked for the identification of affected forest areas. The masking was carried out by taking the burned areas within the forest boundary. The masked-out layers were then validated using reported locations of forest fire obtained from the forest fire history report, which was managed by the Queensland government.

4. Result and discussion

4.1. Factors influencing forest fire

4.1.1. Major fuel distribution

The composition and distribution of major fuel types are crucial determinants of wildfire dynamics, directly influencing ignition potential, fire intensity, and spread patterns. Understanding these fuel types and their characteristics is essential for effective fire management and mitigation strategies (Moor 2019). In Lamington National Park, the diversity of ecosystems is reflected in the variety of fuel types present, each contributing differently to fire behaviour. These ecosystems include rainforests, eucalypt forests, and heathlands, each with unique fuel structures and flammability characteristics (Table 3).

Rainforests in Lamington National Park, such as the complex evergreen mesophyll-notophyll vine forests, possess a distinct fire dynamic due to their typically high moisture levels and dense, multi-layered canopies (Ahmad et al. 2022; QFBC and Health Land and Water 2024). These conditions generally result in lower surface fuel loads and reduced fire spread potential. However, during prolonged dry spells, even rainforests can become vulnerable to ground fires, which can smoulder in the thick organic layers on the forest floor (Goldammer and Center 2017). The presence of species such as *Araucaria cunninghamii* and various vine forests further influences the fire behaviour in these ecosystems, contributing to generally lower flammability compared to other vegetation types (Zimmer et al. 2016; Potts et al. 2022).

Eucalypt forests, although less prevalent in Lamington National Park compared to rainforests, are still significant. These areas are characterised by their tall, often dense stands of eucalyptus trees (Tang et al. 2003). The fuel load in these forests varies but generally includes a significant amount of leaf litter, bark, and woody debris. These fuels can be highly combustible, especially during dry periods, making eucalypt forests susceptible to intense surface fires and canopy fires (Bradstock et al. 2012). Specific eucalypt-dominated areas in the park, such as those with *Eucalyptus orgadophila* and *Eucalyptus grandis*, exhibit varying levels of fire susceptibility based on the moisture content and structure of the vegetation (Eyre 2006).

Heathlands, characterised by low open shrublands to open heaths on elevated rocky substrates, are highly flammable due to their fine, dry fuels such as grasses and small shrubs (Minsavage-Davis et al. 2024; Singh et al. 2024). These areas can facilitate rapid fire spread, especially under windy conditions. The open shrublands in Lamington National Park, particularly those on rocky substrates, are noted for their high susceptibility to fires that can quickly engulf large areas (Del Moral and Walker 2007). The specific composition and distribution of these shrublands contribute significantly to the overall fire risk in the park.

Woodlands in the national park, including those dominated by species such as *Eucalyptus crebra* and *Eucalyptus coolabah*, display variable fire behaviours influenced by factors such as understory composition and weather conditions (Modarres et al. 2024). The open canopy and grassy understory often found in these woodlands can lead to significant surface fires during dry seasons (Bradstock et al. 2012). The variability in fire susceptibility necessitates adaptable fire management strategies tailored to specific woodland types (Sample et al. 2022). These woodlands, although not as extensive as the rainforests, still play a crucial role in the park's overall fire dynamics.

By comprehensively understanding the major fuel types and their fire behaviours, fire management practices can be more effectively tailored to mitigate fire risks and enhance the resilience of diverse ecosystems within Lamington National Park (Clarke et al. 2011; Bradstock et al. 2012; Singh et al. 2024; Singh and Srivastava 2024).

4.1.2. Aspect

Aspect, the compass direction a slope faces, is a critical factor influencing forest fires in Lamington National Park, Queensland, Australia. Understanding the relationship between aspect and fire susceptibility is vital in assessing and mitigating fire risks within this ecologically diverse region (Cruz et al. 2008; Sharples 2009).

Lamington National Park's topography and aspect play a significant role in fire behaviour. In this area, a notable pattern emerges: the north-eastern and eastern aspects tend to be more fire-prone. These aspects receive the most direct sunlight and are typically drier, contributing to increased flammability of vegetation, particularly during dry seasons (Rothermel 1972).

The north-eastern and eastern slopes, due to their orientation, often experience more prolonged sun exposure, resulting in reduced moisture levels in the soil and vegetation. This, in turn, creates conditions conducive to the ignition and rapid spread of fires (Sharples et al. 2010). The combined factors of aspect, climate, and vegetation type in these areas make them more susceptible to forest fires.

Fire management strategies in Lamington National Park must consider the elevated risk associated with north-eastern and eastern aspects. These regions may require increased vigilance, fuel reduction efforts, and targeted fire prevention measures to minimise the impact of wildfires.

The map of aspects in the study area, showing the maximum fire-prone areas in the north-east and east, highlights the importance of recognising these vulnerable zones and tailoring fire management practices accordingly. By understanding the intricate relationship between aspect and forest fire susceptibility, authorities can better protect both the natural ecosystem and local communities in Lamington National Park.

4.1.3. Slope

Slope is a critical terrain feature that significantly influences the behaviour and spread of forest fires in Lamington National Park, Queensland, Australia. Understanding the implications of slope on fire risk is fundamental in developing effective fire management strategies within this ecologically diverse region (Rothermel 1972; Sharples et al. 2010).

The topography of Lamington National Park includes various slopes, which can range from gentle to steep gradients. Slope affects forest fires in several keyways:

1. Fire Spread: Steeper slopes can facilitate the rapid spread of fires (Sharples 2009). As fires burn uphill, they gain momentum due to preheating of fuels and increased fireline intensity (Ren et al. 2022). This can lead to more challenging firefighting efforts and pose greater risks to both the environment and nearby communities.
2. Wind Patterns: Slope can influence local wind patterns. Air tends to rise along upslopes, creating conditions that can accelerate fire spread. It's essential to consider how wind interacts with the terrain, especially on steep slopes, when assessing fire behaviour (Pimont et al. 2012).
3. Fuel Availability: Sloped terrain can affect the distribution of fuels. On uphill slopes, fine fuels and dead vegetation may accumulate, providing additional flammable material for fires (Innocent 2022). This accumulation of fuel can intensify the fire's impact (Bradstock et al. 2012).

The map displaying slope values in the study area, with a maximum value of approximately 84 degrees, signifies areas with steep gradients. These areas are more prone to intense fires, particularly during dry and windy conditions. The recognition of high-slope regions is paramount for prioritising fire prevention and suppression measures.

Fire management strategies in Lamington National Park should consider the influence of slope on fire behaviour and the increased risk associated with steeper terrain. Effective measures may include controlled burns, fuel reduction programs, and strategic planning for fire response on slopes. By accounting for the complexities of slope in fire management, authorities can better protect the park's diverse ecosystem and surrounding communities from the threat of forest fires.

4.1.4. Elevation

Elevation, the measurement of height above sea level, is a pivotal geographic feature that significantly influences forest fires in Lamington National Park, Queensland, Australia. Understanding how elevation impacts fire dynamics is crucial for effective fire risk assessment and management in this ecologically diverse region (Dillon et al. 2011). Scientific knowledge reveals that elevation affects temperature, fuel moisture, and, subsequently, fire behaviour (Lutz et al. 2010; Vanoni et al. 2016). The map displaying elevation values in the study area, with a maximum value of approximately 1189 meters, indicates regions with significant changes in altitude. While higher elevations may be less fire-prone due to cooler and moister conditions, it's important to account for the full spectrum of factors affecting fire behaviour in different elevation zones (Holden et al. 2009). This knowledge is crucial for developing well-informed fire management and prevention strategies that protect the park's unique ecosystem and neighbouring communities.

4.1.4.1. Topographic wetness index (TWI). The Topographic Wetness Index (TWI) is a fundamental terrain parameter that holds significant importance in understanding and managing forest fires within the diverse landscape of Lamington National Park, Queensland, Australia. This index serves as a critical tool for assessing the wetness or dryness of different areas within the park, thereby aiding in the evaluation of fire risk (Moore et al. 1991; Sørensen et al. 2006). Scientific knowledge reveals that TWI is used to assess wetness levels in various park regions, impacting fuel moisture and, consequently, fire behaviour (Beven and Kirkby 1979; Sørensen et al. 2006). The map displaying TWI values in the study area, with values ranging from −0.52 to 21.66, indicates regions with varying degrees of wetness. Effective fire management strategies in Lamington National Park should consider the insights provided by TWI, using this information to develop targeted fire prevention and response measures to safeguard the park's unique ecosystem and local communities.

4.1.5. Distance to road

The scientific importance of estimating distance to roads for forest fire susceptibility mapping cannot be overstated (Syphard et al. 2009). Roads serve as conduits for human activity, which is a significant driver of forest fires worldwide. By accurately quantifying the proximity of forested areas to roads, researchers can better understand the spatiotemporal patterns of fire ignition and spread (Syphard et al. 2011). This information is critical for developing predictive models that identify high-risk areas and prioritise resource allocation for fire prevention and suppression efforts. Additionally, incorporating distance to roads into susceptibility mapping enables a more comprehensive assessment of the human-environment interface, accounting for factors such as land use, accessibility, and infrastructure development, which influence fire dynamics (Syphard et al. 2009).

Furthermore, distance to roads provides valuable insights into the underlying mechanisms linking human activities to fire occurrence. Beyond serving as potential ignition sources, roads can affect fire behaviour by acting as barriers or conduits for fire spread (Boer et al. 2008). Understanding how road networks influence fire dynamics allows for the development of more nuanced fire management strategies, including targeted land-use planning, zoning regulations, and road maintenance practices (Gannon et al. 2023). Moreover, by integrating distance to roads with other environmental variables, such as vegetation type, topography, and weather conditions, researchers can enhance the accuracy and reliability of forest fire susceptibility models, thereby aiding in proactive decision-making and risk mitigation efforts.

4.1.6. Distance to stream

The scientific significance of estimating the distance to streams for forest fire susceptibility mapping is paramount due to the critical role streams play in shaping fire dynamics within ecosystems. Streams act as natural barriers that can impede the spread of fires by creating firebreaks, limiting the availability of combustible materials, and altering local microclimates to reduce the flammability of surrounding vegetation (Dwire and Kauffman 2003; Pettit and Naiman 2007). Accurately assessing the proximity of forested areas to streams provides valuable insights into how the spatial distribution of water bodies influences fire ignition, propagation, and suppression efforts, aiding in the development of predictive models to identify high-risk zones and prioritise fire management strategies effectively.

Integrating distance to streams into forest fire susceptibility mapping enhances our understanding of the intricate interactions between landscape features and fire behaviour. By considering how streams influence fire dynamics alongside other environmental variables such as vegetation types, topography, and weather conditions, researchers can refine susceptibility models to provide more accurate assessments of fire risk (Dwire and Kauffman 2003; Cary et al. 2006). This comprehensive approach enables stakeholders to make informed decisions regarding land management practices, resource allocation for fire prevention and suppression, and the implementation of mitigation measures to reduce the impact of forest fires on ecosystems and communities.

4.1.7. Enhanced vegetation index (EVI)

The Enhanced Vegetation Index (EVI) holds significant scientific importance for forest fire susceptibility mapping due to its ability to quantify vegetation density and health, which are critical factors influencing fire behaviour. EVI measures the density and health of vegetation cover by accounting for factors such as canopy structure, chlorophyll content, and soil background (Huete et al. 2002). Areas with dense, healthy vegetation are typically less susceptible to fire ignition and spread, while sparse or stressed vegetation increases fire risk (Chuvieco et al. 2010). By incorporating EVI data into susceptibility mapping, researchers can accurately assess the spatial distribution of vegetation density and identify areas with heightened fire susceptibility (Huete et al. 2002). This information enables the development of proactive fire management strategies, including targeted fuel reduction efforts, land-use planning, and allocation of firefighting resources.

Below is a map illustrating EVI values ranging from 0.2 to 1, derived from Sentinel-2 data, where higher values indicate denser and healthier vegetation cover (Figure 3). By overlaying this EVI map with other spatial data layers such as topography, weather patterns, and human activities, researchers can generate comprehensive forest fire susceptibility maps that facilitate informed decision-making and effective wildfire management strategies (Jin and Sader 2005).

4.2. Forest fire hazard index using a multi-criteria technique

The Forest Fire Risk Index (Figure 2) was predominantly influenced by the type of major fuel type and aspect, as they were assigned significant weights during the Analytic Hierarchy Process (AHP). Utilising the Natural Break method, the spatial distribution of the computed forest fire hazard raster was classified into five distinct risk levels: very low, low, moderate, high, and very high. Analysis reveals that approximately 4.32% and 29.36% of the total area are encompassed by zones classified as very high and high risk, respectively, indicating notable areas of heightened fire risk within the study area.

4.3. Identification of fire-affected forest areas

The forest fire risk map was generated utilising geospatial technology alongside the Analytic Hierarchy Process (AHP) methodology. Following the determination of final weights for all parameters, the map was converted into raster format and aggregated using a raster calculator within the ArcGIS software platform to delineate zones of potential forest fire risk. To refine the resulting fire zones map and minimise pixel speckling, a majority filter was applied using ArcGIS. The analysis revealed that 4.32% of the area fell within the 'high' fire susceptibility risk zone, followed by 29.36% categorised as moderate risk, and 66.3% as low risk (Table 6).

The analysis revealed a conspicuous concentration of potential forest fire-prone zones, notably clustered in the eastern and south-eastern aspects of the region. Furthermore, areas with high susceptibility to fires were predominantly situated within the lower elevation regions characterised by gentle slopes, particularly prominent in the southern and northern expanse of the study area. This spatial distribution underscores the heightened risk of fire ignition and spreads in regions exhibiting specific aspects and topographical features targeted attention and proactive mitigation measures to safeguard against potential forest fire hazards (Figure 2).

4.4. Validation

The validation of the forest fire risk zone was verified by the fire points of Forest fire history data, which database was created by the Queensland government from the year 1982

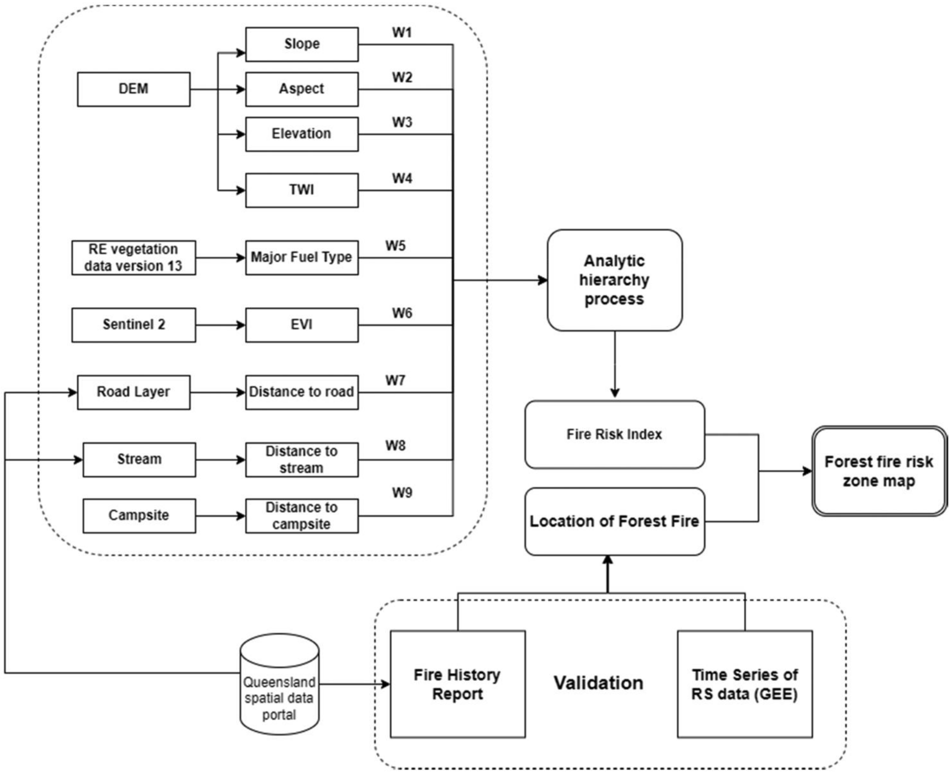

Figure 2. Flowchart adopted to generate forest fire risk zone map (inputs, outputs and process); Wi, the weight of each factor.

to 2018. The fire was very prone in low to moderate elevation ranges, and most of the fire points overlaid in the map were seen as very high and high-risk zones.

In the validation phase of our research article titled ‘Identification of forest fire-prone regions in Lamington National Park using GIS-based multicriteria technique: validation using field and satellite observations’, we employed a rigorous methodology to assess the accuracy and reliability of the forest fire-prone regions identified within the park. Three key figures were generated to validate the GIS-based multicriteria technique utilised in delineating fire-prone areas.

The Time since last burns (monthly) Map (Figure 3), offering a comprehensive temporal analysis of fire occurrence and frequency across the landscape. This figure provides critical insights into the temporal dynamics of fire events, aiding in fire management strategies and ecological monitoring efforts within the study area. The visualisation of fire frequency over time enhances our understanding of fire regimes and their implications for ecosystem dynamics, thus contributing to the broader scientific understanding of fire ecology.

The Burned Area Map (Figure 4), visually depicts the extent and distribution of areas affected by past fires within Lamington National Park. This map highlights the spatial footprint of historical fire events, facilitating the identification of fire-prone zones and informing future fire management planning. The delineation of burned areas serves as a valuable tool for assessing fire risk and guiding efforts to mitigate the impact of wildfires on the park’s biodiversity and ecological processes.

Table 6. Comprehensive comparison of wildfire susceptibility mapping studies using Analytical Hierarchy Process (AHP) and advanced methods, highlighting key factors, validation techniques, and findings across various regions.

Study	Method	Region	Factors used	Validation method	Key findings
(Kumari and Pandey 2020)	AHP	Palamau Tiger Reserve	Slope, Aspect, Vegetation	Field validation	Identified high-risk areas
(Sivrikaya and Küçük 2022)	AHP	Turkey	Elevation, Proximity to Roads	Historical fire data	Highlighted fuel load as a key factor
(Çoban and Erdin 2020)	AHP	Bucak Forest, Turkey	Slope, Aspect, Proximity to Roads, Vegetation Types, Wind	Burned area analysis	Wind direction and vegetation density significantly impacted fire spread.
(Milanović et al. 2020)	Logistic Regression + AHP	Eastern Serbia	Distance to Urban Areas, Elevation, Vegetation, Precipitation	Satellite imagery and fire points	Combined statistical and AHP models for higher accuracy in fire prediction.
(Achu et al. 2021)	Random Forest	Southern India	Land Use, Soil Moisture, Vegetation Density, Climate Data	Kappa coefficient	Machine learning provided superior performance compared to traditional models.
(Mohajane et al. 2021)	Random Forest + SVM	Mediterranean Area, Morocco	Topography, Climate Data, Fuel Load	ROC-AUC	Found that Random Forest had the highest predictive accuracy.
(Glushkov et al. 2021)	Participatory Mapping + AHP	Russia	Vegetation Types, Elevation, Fire History	Fire history points and stakeholder review	Integrated participatory mapping with AHP for community-based risk assessments.
This study	AHP + Field Validation	Lamington National Park	Enhanced Vegetation Index, Topographic Wetness Index, Historical Fire Data	Sentinel-2 and field observations	ntegrated subtropical-specific variables; identified east and north aspects as high-risk areas.

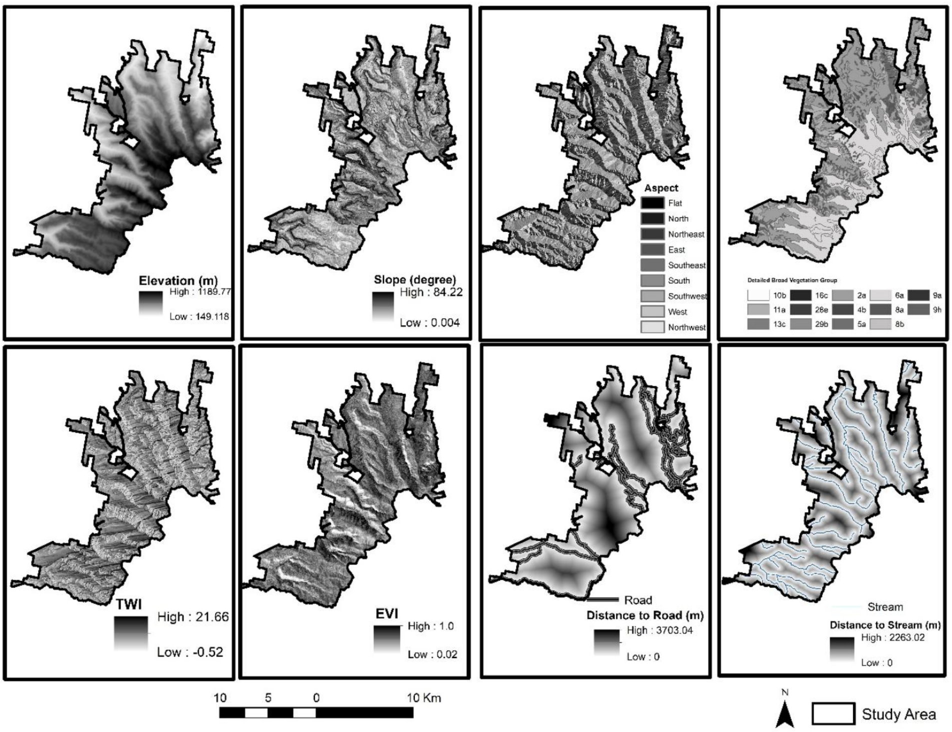

Figure 3. Forest fire susceptibility parameters used in this study include (a) elevation, (b) slope, (c) aspect, (d) major fuel type distribution, (e) topographic wetness index (TWI), (f) Enhanced vegetation index (EVI), (g) distance to roads, and (h) distance to streams.

Overlays fire history points onto the final forest fire risk index zone map, demonstrating the spatial correspondence between historical fire events and identified fire-prone zones. Notably, a significant proportion of the fire history points coincide with areas classified as high-risk zones, affirming the accuracy of the risk assessment methodology employed in our study. Furthermore, the spatial consistency between time since last burn and burned area maps with the final risk index zones underscores the reliability of the multicriteria approach in predicting fire-prone regions within the park.

To validate the susceptibility mapping, fire history data comprising 79 fire points were overlaid with the fire risk zones identified in the study. The analysis revealed that 70.9% of the fire points fell within high-risk zones, while 24.1% were located in moderate-risk zones. Only 5.1% of the fire points were observed in low-risk areas (Table 7).

Table 7. Distribution of fire points across risk zones.

Risk zone	Number of fire points	Percentage of total fires (%)
High risk	56	70.9
Moderate risk	19	24.1
Low risk	4	5.1

This distribution aligns with the predicted fire susceptibility model, demonstrating its effectiveness in identifying high-risk zones. The strong correlation between historical fire occurrences and high-risk areas validates the robustness of the applied methodology and its utility in fire management and mitigation strategies.

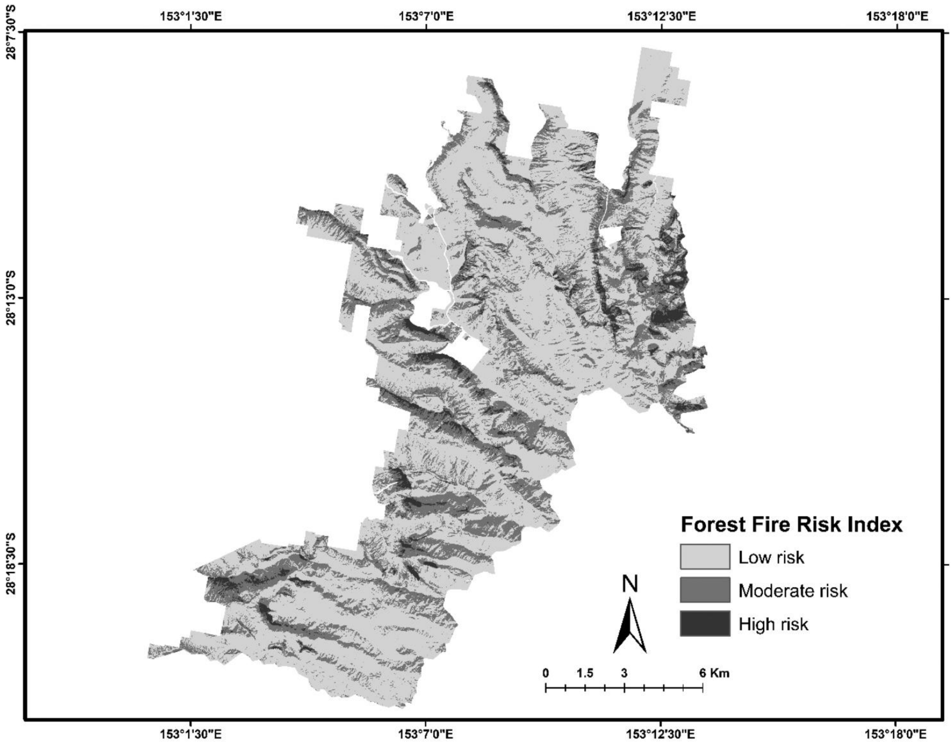

Figure 4. Spatial distribution of forest fire risk zones in the study area, categorised into very low, low, moderate, high, and very high risk. The map highlights a concentration of high and very high fire susceptibility zones primarily in the Eastern and South-Eastern regions, as well as in lower elevation areas with gentle slopes in the Southern and Northern parts.

Figure 5. Field photographs of fire patches identified in the study area, highlighting regions with a high risk of fire. The images illustrate the severity and spread of fire-prone zones, as determined by the study's result.

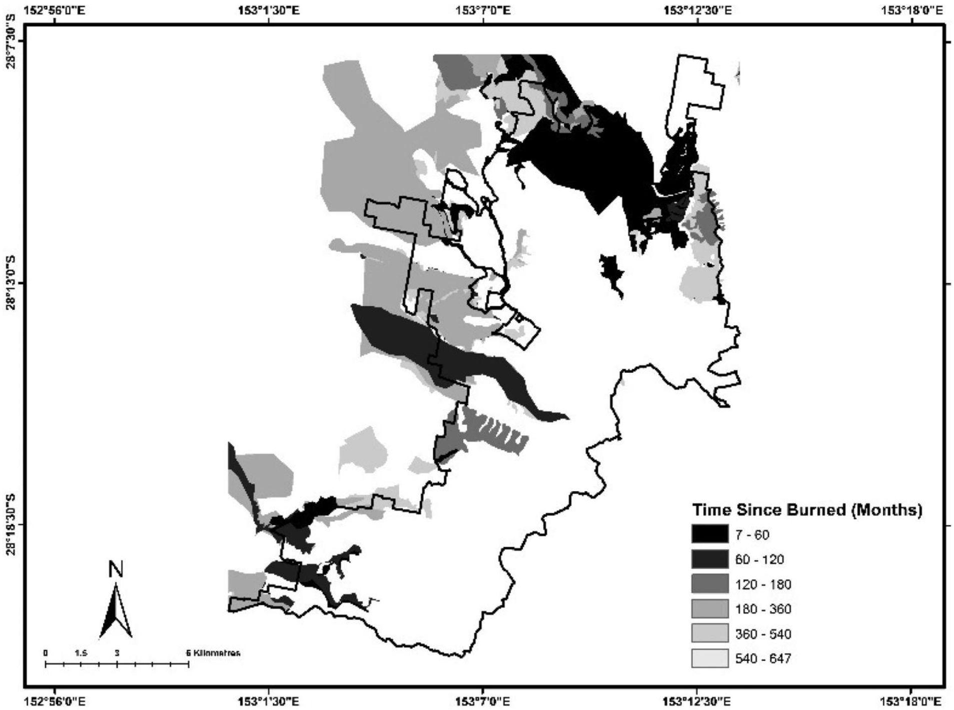

Figure 6. Time since last burns (monthly) map—depicting the temporal dynamics of fire occurrence and frequency across the studied landscape, providing critical insights for fire management and ecological monitoring.

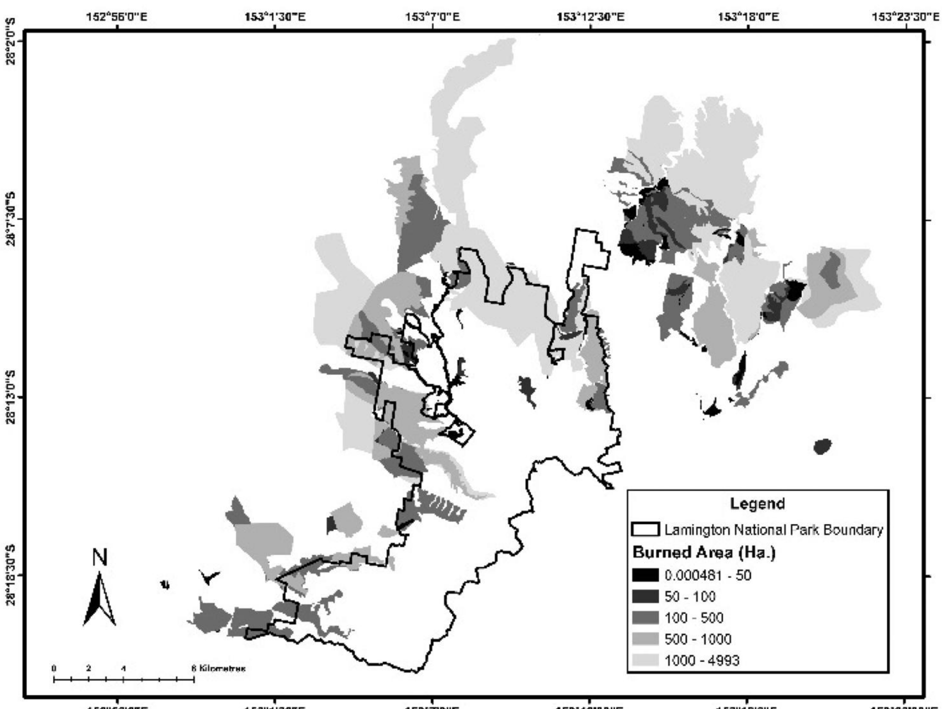

Figure 7. Burned area map—visualising the extent and location of areas affected by past fires.

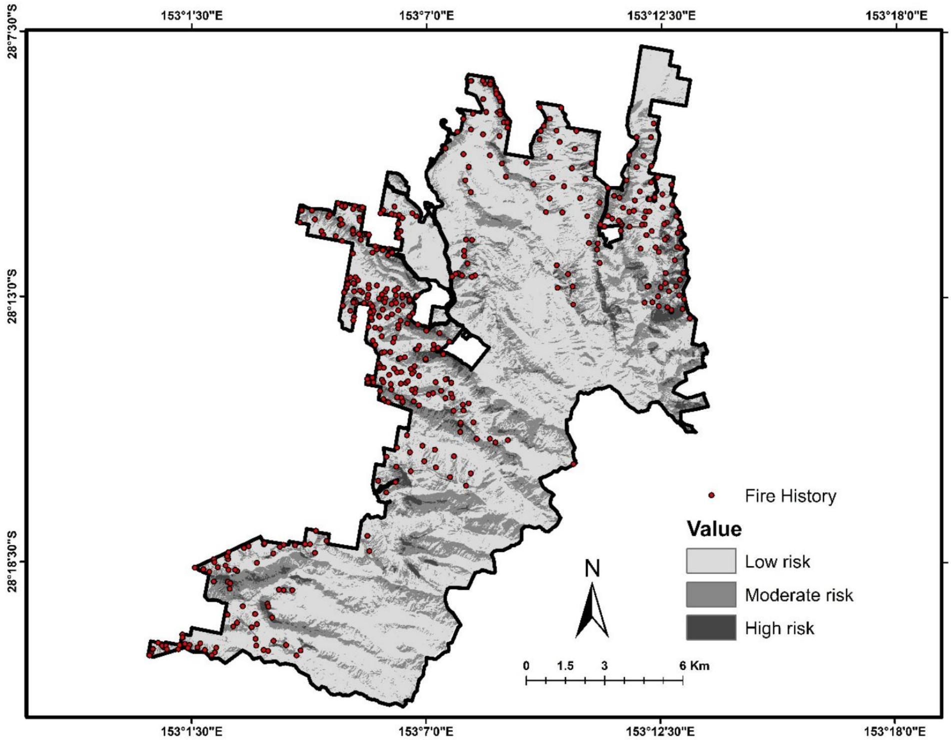

Figure 8. Fire history data overlaid on forest fire risk zone.

In conclusion, the validation results presented in this research article validate the effectiveness of the GIS-based multicriteria technique in identifying forest fire-prone regions in Lamington National Park. The integration of field and satellite observations enhances the accuracy and reliability of our assessment, providing valuable insights for fire management and ecological conservation efforts in the park and contributing to the advancement of scientific knowledge in the field of fire ecology.

4.5. Comparison with advanced methods

While advanced machine learning models such as Random Forest and deep learning algorithms like U-Net have been applied in wildfire susceptibility studies, they often require extensive computational resources and lack interpretability for policy-making and on-ground implementation. In contrast, AHP offers a transparent and straightforward approach, particularly suitable for integrating field data with geospatial indices in regions where resources or computational capacity may be limited. Future studies could build upon this work by combining AHP with machine learning models for enhanced accuracy and scalability.

5. Conclusion

The primary purpose of the study is to identify fire-affected forest stretches in the Lamington National Park, Queensland, Australia, using a multi-criteria analysis approach, specifically the AHP model, which facilitates the multi-source data combinations. The adopted methodology spatially analyses the 9 physical parameters, namely Surface slope (S), Aspect (A), Elevation (E), Enhanced vegetation index (EVI), Topographic wetness index (TWI), Major fuel type (MFT), Distance to road (DR), Distance to stream (DS) and Distance to camping site (CS). After the application of the AHP model, the higher weights were assigned to Major fuel type. The raster calculation in GIS in the environment using assigned weights and risk level-wise rating score and post masking results to visualise fire-prone forest regions.

The present case study in Lamington National Park has revealed the Forest fire-prone areas. The results depicted that the forest fire reaches in the north and east of the Lamington National Park are susceptible to fire which is mainly governed by very dry and hot conditions.

In looking ahead, the outcomes of this study hold significant implications for future research directions and management approaches. Firstly, there is a pressing need for the refinement of methodologies utilised herein to bolster the precision and reliability of forest fire susceptibility mapping. This could involve integrating additional variables and employing more advanced analytical techniques to enhance predictive capabilities. Secondly, incorporating temporal analysis through the utilisation of time-series satellite imagery and historical climate data could offer deeper insights into the evolving nature of forest fire susceptibility over time, thereby enabling the implementation of adaptive management strategies. Moreover, considering the escalating influence of climate change on fire regimes, future investigations should incorporate climate change projections to anticipate how shifting environmental conditions may alter susceptibility patterns. Concurrently, community engagement and education initiatives must be prioritised to empower local communities in fire-prone areas and foster a culture of fire prevention and preparedness. Furthermore, the identification of fire-prone areas underscores the importance of implementing targeted risk reduction measures such as prescribed burning and fuel management. These efforts should be integrated into broader landscape-scale planning and management frameworks to maximise effectiveness and resilience. Lastly, continuous monitoring and evaluation are paramount to assess the efficacy of management interventions and adapt strategies in response to changing conditions. By addressing these future implications, stakeholders can collaboratively work towards enhancing wildfire management strategies, safeguarding ecosystems, and mitigating the impacts of wildfires on communities and biodiversity.

Future research could extend this work by incorporating machine learning or deep learning methods, such as Random Forest or U-Net, to compare and validate the AHP-derived fire risk index. Additionally, temporal analyses using time-series satellite imagery and dynamic environmental variables, such as real-time meteorological data, could provide deeper insights into evolving fire susceptibility patterns. Integrating climate change projections could also enable the development of adaptive fire management strategies for subtropical ecosystems like Lamington National Park.

Author contributions

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

Institutional review board statement

Not applicable.

Availability of data and material/data availability

All data of this study are provided in the results and raw data can be made available on request.

Ethical considerations

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. Field observations, including the use of field photographs, were conducted with the necessary permissions from the appropriate authorities to ensure the protection of the natural environment and adherence to legal and ethical standards.

The use of satellite data, specifically from Sentinel-2, 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. The research, including the use of field photographs, was designed to contribute to the understanding and management of forest fire risks in Lamington National Park, with the ultimate goal of enhancing conservation efforts and supporting sustainable environmental practices.

Disclosure statement

No potential conflict of interest was reported by the authors.

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