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FOREST FIRE TRENDS IN INDONESIA AND AUSTRALIA: LESSONS LEARNED AND MITIGATION STRATEGIES

Evizal Abdul Kadir[1], Wan Aezwani Wan Abu Bakar[2], Sri Listia Rosa[3] and Hitoshi Irie[4]

[1, 3]Department of Informatics, Faculty of Engineering, Universitas Islam Riau, Pekanbaru, 28284, Indonesia
[2]Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Terengganu, 21300 Malaysia
[4]Center for Environmental Remote Sensing, Chiba University, Chiba, 263-8522 Japan

[1]https://orcid.org/0000-0003-1258-3840, [2]https://orcid.org/0000-0002-5871-401X
[3]https://orcid.org/0000-0002-4367-5396, [4]https://orcid.org/0000-0001-5782-3292

Email: evizal@eng.uir.ac.id, wanaezwani@unisza.edu.my, srilistiarosa@eng.uir.ac.id, and hitoshi.irie@chiba-u.jp

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ABSTRACT

Forest fires present significant environmental, economic, and social challenges in both Indonesia and Australia, with each country exhibiting different causes and effects. In Indonesia, forest and peatland fires are frequently driven by land-use changes, agricultural practices, and extended dry seasons, particularly during El Niño events. In contrast, Australia experiences intense bushfires primarily fueled by extreme heat, drought, and natural ignition sources such as lightning. This research analyses fire trends in both countries, identifying key factors that contribute to their frequency and severity. Lessons learned from past incidents, including the 2019–2020 Australian bushfire crisis and Indonesia's recurrent peatland fires, emphasize the need for improved fire management strategies. Various mitigation approaches, such as early warning systems, controlled burns, policy regulations, and community-based prevention programs, are discussed. In addition, advancements in remote sensing, artificial intelligence, and IoT based monitoring systems are examined as potential solutions. This comparative analysis highlights the importance of regional cooperation, adaptive policies, and sustainable land management to mitigate future fire risks. Learning from each nation's experiences, policymakers and stakeholders can develop more effective strategies for combating forest fires and reducing their long-term effects.

I. INTRODUCTION

Forest fires have long been a critical environmental challenge, resulting in wide-spread destruction of ecosystems, human settlements, and economies. In recent years, the increasing frequency and severity of these fires have raised global concern, particularly in regions vulnerable to prolonged dry seasons and extreme weather conditions. Indonesia and Australia are two of the most affected countries, experiencing recurrent forest fires driven by different but interconnected factors. Although Indonesia's fires are often linked to human activities such as land-clearing and peatland drainage, Australia's bushfires are primarily fueled by climatic conditions, including heatwaves, droughts, and strong winds. Despite these differences, both nations face the escalating challenge of mitigating the effects of increasingly severe fire seasons intensified by climate change [1].

Indonesia's forest and peatland fires present a persistent challenge, particularly in provinces such as Sumatra and Kalimantan. These fires are mainly caused by slash-and-burn agricultural practices that, despite being illegal, continue due to economic pressures and inadequate law enforcement. Peatland fires are particularly difficult to manage because they can smolder underground for long periods, releasing significant amounts of carbon dioxide and causing severe transboundary haze. This haze affects not only Indonesia but also neighboring countries such as Malaysia and Singapore, resulting in diplomatic tensions and public health crises. Despite various fire prevention programs and policies, Indonesia continues to struggle with effective fire management and regulatory enforcement [2].

In contrast, Australia faces a different fire regime, characterized by intense and rapidly spreading bushfires. The country's natural vegetation, including eucalyptus forests, contains volatile oils that make it highly combustible. Climate change has exacerbated the risk, with rising temperatures and prolonged droughts creating ideal conditions for catastrophic fires. The 2019–2020 Black Summer bushfires underscored the devastating consequences of these fires, burning over 18 million hectares, destroying thousands of homes, and killing or displacing nearly three billion animals. Unlike in Indonesia, where human activities play a significant role in fire ignition, Australia's bushfires are often triggered by natural causes such as lightning strikes. However, the severity of these fires has sparked renewed discussions about fire management strategies, such as controlled burns, land-use policies, and the integration of Indigenous fire knowledge in prevention efforts [3]. The increasing intensity of forest fires in both Indonesia and Australia highlight the urgent need for comprehensive fire management strategies that encompass early detection, prevention, and suppression efforts.

This research aims to analyze fire trends in both countries, drawing lessons from past experiences and exploring mitigation strategies. Comparing different fire management approaches, this study seeks to identify best practices that can be implemented to enhance fire prevention and response efforts. In addition, the study examines the role of technological advancements, such as satellite monitoring, artificial intelligence, and Internet of Things (IoT) based early warning systems, in improving fire management capabilities [4]. Through a comparative analysis of Indonesia and Australia, this study contributes to the broader discourse on climate resilience, sustainable land management, and international cooperation in mitigating forest fire risks [5]. This research examines the trends of forest fire behavior in Indonesia and Australia to inform mitigation strategies. Data on fire incidents were collected from ground sensors and satellite information provided by the National Aeronautics and Space Administration (NASA) Earth Data for both regions. The data were analyzed to identify trends, and a proposed action plan for future forest fire mitigation and management.

II. THEORETICAL REFERENCE

Forest fires are a persistent environmental issue in both Indonesia and Australia, though the causes, patterns, and consequences differ between the two regions. Research indicates that Indonesia's forest fires are primarily anthropogenic, driven by land-use changes and agricultural practices such as slash-and-burn cultivation [6], [7]. The severity of these fires is particularly pronounced in peatland areas, where they can smolder underground for months, releasing massive amounts of carbon into the atmosphere [8], [9]. Studies show that fire incidents in Indonesia often peak during El Niño years when prolonged dry seasons create conditions conducive to fire spread [10], [11]. In contrast, Australia's forest fires, commonly referred to as bushfires, are largely influenced by climatic and ecological factors. Research reveals that fire seasons in Australia have in-testified due to rising temperatures and extended drought periods [12]. The 2019–2020 Black Summer bushfires, which scorched over 18 million hectares, exemplified the in-creasing severity of fire events, with researchers linking this phenomenon to climate change [13], [14].

Unlike Indonesia, where human activities are the primary cause of fire ignition, Australian bushfires are typically triggered by natural events such as lightning strikes, with vegetation and dry conditions providing ample fuel sources [15]. The environmental, social, and economic consequences of forest fires in both Indonesia and Australia have been extensively studied. In Indonesia, haze from forest fires has been a persistent problem, leading to severe air pollution that affects millions across Southeast Asia [16-18]. Studies have linked exposure to this haze with respiratory illnesses, school closures, and economic losses, especially in the agriculture and tourism sectors [19]. In addition, fires in peatland areas contribute significantly to global carbon emissions, worsening climate change [20]. In Australia, the effects of bushfires are similarly cata-strophic. The 2019–2020 Black Summer fires resulted in the loss of nearly three billion animals, including many endangered species [21]. In addition to biodiversity loss, studies have emphasized the economic consequences of bushfires, which include the destruction of homes, infrastructure, and agricultural land [22].

Furthermore, long-term health effects from smoke exposure have been documented, with increases in respiratory and cardio-vascular diseases following major fire events [23]. To manage forest fires in both countries, several mitigation strategies have been implemented. In Indonesia, fire prevention efforts have primarily focused on regulatory measures, such as banning slash-and-burn practices and promoting peatland restoration initiatives [24]. However, enforcement challenges and land-use conflicts have limited the effectiveness of these policies [25]. Some studies recommend the involvement of local communities in fire prevention through sustainable land management and agroforestry practices [26]. In Australia, traditional fire management strategies have relied on con-trolled burns, also known as prescribed burning, to reduce fuel loads and lower the risk of large-scale fires [27]. Nonetheless, recent research suggests that climate change is di-minishing the effectiveness of controlled burns, as fire seasons are becoming longer and more unpredictable [28]. Indigenous fire management practices, which employ low intensity burning to maintain ecosystem balance, have gained increasing attention as a promising solution [29].

The application of technology in forest fire monitoring and mitigation has seen significant advancements in recent years. Remote sensing and satellite imagery have proven essential in detecting fire hotspots and assessing fire severity in both Indonesia and Australia [30]. In addition, artificial intelligence (AI) and machine learning models are being developed to predict fire risks based on factors such as weather patterns, fuel availability, and historical fire data [31]. In Indonesia, pilot projects for IoT-based early warning systems have been implemented to monitor peatland moisture levels and detect fire risks in real time [20], [32]. In Australia, investments in drone technology and auto-mated fire detection systems aim to enhance firefighting efforts [30]. Given the transboundary nature of forest fires, international cooperation is vital for effective fire management. Indonesia has engaged in Association of Southeast Asian Nation (ASEAN)-led initiatives, such as the ASEAN Agreement on Transboundary Haze Pollution, to tackle regional haze issues [33], [34].

However, challenges persist in policy enforcement and stakeholder compliance [35]. In contrast, Australia has collaborated with global research institutions and climate organizations to enhance bushfire prediction and response strategies [36]. The country has also actively shared its fire management expertise with other fire-prone regions, including California and Southern Europe [37]. This research compares forest fire trends in Indonesia and Australia, highlighting similarities, differences, and key drivers behind fire occurrences. The primary dataset for this study is sourced from the NASA Earth Data Portal (https://earthdata.nasa.gov/) [38]. Specifically, relevant satellite datasets, including the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) are accessed based on the research objectives.

Data parameters such as geolocation (latitude and longitude), intensity measurements (including temperature anomalies), fire radiative power, precipitation rates, and timestamps are downloaded in CSV format as available in the database. The data collected from NASA and selected case studies are categorized into key themes: fire causes, environmental impact, and mitigation strategies. The analysis of trend and historical fire data reveals patterns in fire frequency, intensity, and geographical distribution over the past five years. In addition, existing fire prevention and suppression policies in both countries are assessed for their effectiveness, challenges, and opportunities for improvement [39].

III. MATERIALS AND METHODS

When active fire suppression amidst bushfire intensity is considered, it is suggested that only surface cooling be applied, as evaporated water vapor dissipates quickly and does not significantly affect flame temperature. When fire point theory is utilized and the external radiant and convective heat flux is calculated, the critical flow rate (CF) for wildfire scenarios can be determined using the following Equation (1) [39]. The CF represents the flow rate of water needed to extinguish a burning surface, assuming an infinite period. However, because the length and depth of an active wildfire front fluctuate over time, affected by terrain, wind, fuel structure, and fuel geometry [21], the CF is calculated only for a specific moment.

$$CF = m^{H}{}_{water,cr,0} + \frac{q^{h}E}{\eta_{water}\ x\ L_{v,water}} \tag{1}$$

where:

$m^{H}{}_{water,cr,0}$ is the critical water application rate, assuming no external heat flux and identified as ≈ 0.0129 $Lm^{-2}s^{-1}$ [39],
η_{water} is the efficiency of water application, defined as the portion of water leaving the firefighting branch and contributing to fire extinguishment, conservatively assumed to be 0.7,
$L_{v,water}$ is the enthalpy change of water, identified as 2640 kJkg^{-1}, and $q^{h}E$ is external heat flux, calculated by (2).

$$q^{h}E = \left(\frac{0.27\ x\ 1}{(2\ x\ L_f + D)}\ x\ \tau\phi\right) + \left(h\ x\left(T_g - T_{fuel}\right)\right) \tag{2}$$

where:

I am fire line intensity in kWm^{-1}, calculated using Byram's fire line intensity equation and Equation (3),
L_f is flame length in m, calculated using Equation (4),
D is depth of the active flame, measured in m,
τ is atmospheric transmissivity, assumed to be 1 due to the proximity of the unburned fuel to the flames,
ϕ is the view factor, expected to be 1 due to the proximity of the unburned fuel to the flames,
h is the convective heat transfer coefficient, set at 0.077 kW/m^2K and assuming a forced convection and air velocity of 10 ms^{-1}[1],
T_g is the gas temperature of the flame, assumed to be 1090 K and representative of siege wildfire conditions, and
T_{fuel} is the fuel temperature of the fuel, assumed to be 588 K, which corresponds to the ignition surface temperature for pine-needle fuel beds [1].

$$I = \frac{HW\ R_0\ S}{36} \tag{3}$$

where:

H is the effective heat of combustion, assumed to be 18,600 kJkg^{-1},
W is the total fuel load, measured in tha^{-1}, considering fine fuels typically less than 6 mm in diameter, and

$R_0\ S$ is the forward rate of spread corrected for slope, measured in kmh^{-1} and calculated using Equation (5). Note that terrain affects $R_0\ S$, where the slope is assumed to be flat for the purposes of the study.

In addition, flame length (L_f) is defined by

$$L_f = \frac{13R_0\ S + 0.24W}{2} \tag{4}$$

$$R_0\ S = 0.0012\ (Define\ FDI) \tag{5}$$

To identify a suitable dataset aligned with the study objectives, NASA's Earth Data were accessed using Python programming to select appropriate spatial and temporal ranges. The dataset includes relevant variables such as fire intensity indicators and geographic coordinates. The raw data were pre-processed to convert file formats, correct missing or erroneous entries, and standardize units for further analysis. During preprocessing, the data were corrected to remove null values, duplicate entries, and anomalous data points. Fire detections with longitude and latitude coordinates were extracted from the dataset and aligned according to specific time intervals (daily, weekly, or monthly) for trend analysis. Intensity analysis focused on temperature anomalies, precipitation rates, and radiative energy using both statistical and spatial approaches. This included calculating the mean, maximum, minimum, and standard deviation of intensity values across selected regions and time periods. This study also conducted time-series analysis to identify patterns in intensity changes over time and to examine relationships between fire intensity and external factors, such as climatic indices and vegetation cover.

Python served as the primary software for all statistical analyses in this research. Finally, to validate the NASA Earth dataset, a monitoring station was established to collect ground-based environmental parameters, including temperature, humidity, wind direction, wind speed, and rain intensity. Figure 1 shows the station configuration.

Figure 1: A station in the campus to detect environmental data.
Source: Authors, (2026).

Geospatial analysis and mapping were performed to visualize the spatial distribution of fire intensity. The corrected geolocation and intensity data were imported into Geographic Information System (GIS) software using Python's Geo-Pandas and Folium libraries. The study generated location maps to display intensity distributions, which were categorized into five levels (0–100) ranging from weak fire generation potential to high forest fire ignition potential. Additional pinpoint maps were created to identify precise locations of significant fire events or anomalies. Temporal maps illustrated changes in intensity over time across different geographic regions. To provide context, the maps included overlay layers such as administrative boundaries, land cover classifications, and elevation data. The processed data and visualizations were cross verified with ground measurements from the local monitoring station, as shown in Figure 1.

This validation compared the NASA Earth Data with the locally collected dataset containing environmental parameters. Finally, the study interpreted the mapped and analysed data to identify patterns in intensity variations. A sample dataset from Indonesia, extracted from NASA Earth Data for December 2024, is presented in Table 1. In total, the study incorporated 251,031 datasets collected over a 5-year period. Fire hotspot data for Indonesia and Australia were obtained from NASA's Fire In-formation for Resource Management System (FIRMS). This system utilizes MODIS and VIIRS sensors to provide satellite-based active fire detections. The dataset includes critical information such as the geographic coordinates (latitude and longitude) of each fire hotspot, along with the date and time of detection, and fire radiative power (FRP), which indicates fire intensity and the confidence levels of detection.Following data acquisition, preprocessing steps were conducted to filter out low-confidence detections, ensuring that only reliable hotspots were analyzed.

The data were then sorted by country and organized according to temporal parameters for trend analysis. Statistical analyses were performed to determine the total number of hotspots and average fire intensity over specific time intervals (both monthly and yearly). Various graphical representations, including time-series plots, were used to visualize fluctuations in fire occurrences over time in Indonesia and Australia. The geographic distribution of fire hotspots was mapped using GIS tools. Heat and point maps were generated to illustrate the spatial concentration and intensity of fires across different regions. These visualizations facilitated a comparative analysis between the two countries, highlighting patterns in fire activity, identifying high-risk areas, and offering insights into seasonal and regional trends. The findings enhance our under-standing of fire dynamics and inform improved fire management and mitigation strategies in both countries. As Table 2 shows, the analysis included data collected for Australia during December 2024.

Table 1: Data from MODIS of fire data in Indonesia.

No	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_t31	frp	daynight
1	0.00316	10.242.418	305.63	01.44	01.19	01/12/24	302	Terra	MODIS	6	6.1NRT	281.87	0.3174	D
2	-150.351	12.340.599	311.78	1	1	01/12/24	612	Aqua	MODIS	38	6.1NRT	291.00	06.04	D
3	-150.479	12.339.719	317.45	1	1	01/12/24	612	Aqua	MODIS	71	6.1NRT	291.18	11.01	D
4	-853.614	12.276.443	307.19	01.22	01.01	01/12/24	1342	Terra	MODIS	71	6.1NRT	273.45.00	11.21	N
5	-257.555	12.276.915	317.38.00	01.02	01.09	01/12/24	1342	Terra	MODIS	93	6.1NRT	272.61	0.9243	N
6	-257.708	12.136.852	310.02.00	01.02	01.09	01/12/24	1342	Terra	MODIS	69	6.1NRT	275.58.00	0.5979	N
7	0.66122	11.756.352	306.06.00	01.53	02.22	02/12/24	202	Terra	MODIS	51	6.1NRT	280.99	0.3493	D
8	-300.437	12.019.854	309.61	01.43	0.084	02/12/24	204	Terra	MODIS	0	6.1NRT	287.68	25.07.00	D
9	-300.838	1.201.927	308.58.00	01.43	0.084	02/12/24	204	Terra	MODIS	0	6.1NRT	287.18.00	22.06	D
10	-257.374	12.137.231	307.68	03.51	0.094	02/12/24	204	Terra	MODIS	66	6.1NRT	274	44.43.00	D
11	-121.363	3.18.418.903	306.78	01.35	01.15	02/12/24	514	Aqua	MODIS	0	6.1NRT	287.56.00	0.2673	D
12	0.48566	12.799.583	315.24.00	1	1	03/12/24	104	Terra	MODIS	54	6.1NRT	294.26.00	08.52	D
13	3.3701	12.800.458	312.19.00	1	1	03/12/24	104	Terra	MODIS	43	6.1NRT	294.39.00	06.01	D
14	-146.326	12.743.544	313.41.00	1	1	03/12/24	104	Terra	MODIS	0	6.1NRT	292.97	06.48	D
15	-258.409	12.137.563	342.07.00	01.11	01.05	03/12/24	1325	Terra	MODIS	100	6.1NRT	288.51.00	54.32.00	N
16	-257.477	12.137.447	325.42.00	01.11	01.05	03/12/24	1325	Terra	MODIS	100	6.1NRT	287.53.00	26.63	N
17	-256.772	12.137.828	303.44.00	01.01	1	03/12/24	1815	Aqua	MODIS	55	6.1NRT	276.43.00	07.08	N
18	-257.658	121.377	316.13.00	01.01	1	03/12/24	1815	Aqua	MODIS	93	6.1NRT	276.82	0.7236	N
19	-257.79	1.213.858	300.34.00	01.01	1	03/12/24	1815	Aqua	MODIS	23	6.1NRT	277.89	06.11	N
20	-257.052	12.216.519	303.69	1	1	03/12/24	1815	Aqua	MODIS	41	6.1NRT	283.23.00	06.09	N
21	-287.184	122.174	302.34.00	1	1	03/12/24	1815	Aqua	MODIS	43	6.1NRT	283.12.00	04.08	N
22	-264.218	12.136.949	304	01.05	01.21	04/12/24	145	Terra	MODIS	33	6.1NRT	277.72	0.2715	D
23	-862.805	12.222.207	312.05.00	02.17	01.43	04/12/24	147	Terra	MODIS	15	6.1NRT	290.74	16.43	D
24	-46.911	12.025.997	321.11.00	01.09	01.04	04/12/24	631	Aqua	MODIS	75	6.1NRT	297.33.00	11.13	D
25	-258.491	12.137.611	351.02.00	01.01	1	06/12/24	126	Terra	MODIS	96	6.1NRT	291.82	60.39.00	D
26	-386.919	12.239.924	308.32.00	01.02	01.01	06/12/24	126	Terra	MODIS	41	6.1NRT	283.34.00	04.06	D
27	-258.618	12.137.487	314.59.00	01.01	1	06/12/24	126	Terra	MODIS	74	6.1NRT	290.37.00	0.3527	D
28	-257.608	12.137.737	340.26.00	01.01	1	06/12/24	126	Terra	MODIS	92	6.1NRT	293.16.00	39.35.00	D
29	-257.736	12.138.614	313.03.00	01.01	1	06/12/24	126	Terra	MODIS	70	6.1NRT	291.03.00	06.09	D
30	131.589	9.950.997	307.21.00	01.06	01.03	06/12/24	304	Terra	MODIS	63	6.1NRT	285.09.00	04.42	D

Source: Authors, (2026).

Although this research offers valuable insights into forest fire trends and mitigation strategies, it does have limitations, specifically in its reliance on secondary datasets. This study depends on existing literature and reports, which may carry inherent biases or gaps. Variability in fire data collection, stemming from differences in methods and reporting standards between Indonesia and Australia, may affect direct comparisons. In addition, the effects of climate change is recognized as uncertain in this research, acknowledging that future fire trends may be influenced by unpredictable climate factors beyond current models. All data sources utilized in this study are publicly available, with appropriate citations provided to acknowledge the original research.

Table 2: Data from MODIS of fire data in Australia.

No	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_t31	frp	daynight
1	0.00316	10.242.418	305.63	01.44	01.19	01/12/24	302	Terra	MODIS	27	6.1NRT	281.87	0.3181	D
2	-150.351	12.340.599	311.78	1	1	01/12/24	612	Aqua	MODIS	38	6.1NRT	291.00	06.04	D
3	-150.479	12.339.719	317.45	1	1	01/12/24	612	Aqua	MODIS	0	6.1NRT	291.18.00	11.01	D
4	-257.555	12.276.915	317.38.00	01.02	01.09	01/12/24	1342	Terra	MODIS	93	6.1NRT	272.61	0.92432	N
5	-257.708	12.136.852	310.02.00	01.02	01.09	01/12/24	1342	Terra	MODIS	69	6.1NRT	275.58.00	0.59792	N
6	-853.614	12.276.443	307.19.00	01.22	01.01	01/12/24	1342	Terra	MODIS	71	6.1NRT	273.45.00	11.21	N
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8	-300.437	12.019.854	309.61	03.51	0.094	02/12/24	204	Terra	MODIS	66	6.1NRT	274	44.43.00	D
9	-300.838	1.201.927	308.58.00	01.43	0.084	02/12/24	204	Terra	MODIS	0	6.1NRT	287.68	25.07.00	D
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11	-121.363	13.418.903	306.78	01.35	01.15	02/12/24	514	Aqua	MODIS	0	6.1NRT	287.56.00	0.26736	D
12	3.37014	12.800.458	312.19.00	1	1	03/12/24	104	Terra	MODIS	43	6.1NRT	294.39.00	06.01	D
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22	-264.218	12.136.949	304	01.05	01.21	04/12/24	145	Terra	MODIS	33	6.1NRT	277.72	0.2715	D
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28	-257.608	12.137.737	340.26.00	01.01	1	06/12/24	126	Terra	MODIS	92	6.1NRT	293.16.00	39.35.00	D
29	-257.736	12.138.614	313.03.00	01.01	1	06/12/24	126	Terra	MODIS	70	6.1NRT	291.03.00	06.09	D
30	131.589	9.950.997	307.21.00	01.06	01.03	06/12/24	304	Terra	MODIS	63	6.1NRT	285.09.00	04.42	D

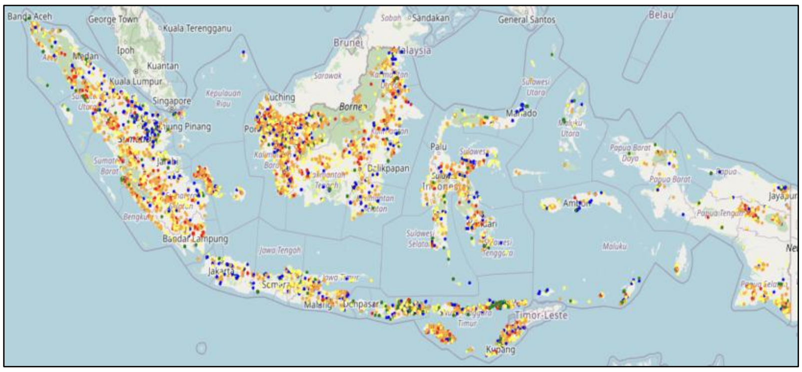
Source: Authors, (2026).

IV. RESULTS AND DISCUSSIONS

Based on the analyzed data, the results map fire hotspots across Indonesia, as visualized in Figure 2. The maps employ a color-coded classification system, itemized as follows:

- Blue: Low fire potential
- Green: Moderate
- Yellow: Elevated
- Pink: High
- Red: Very high fire potential (80–100 confidence level).

The areas with the highest fire intensity, indicated by pink and red dots, are in central Indonesia, specifically on Kalimantan and Sumatra Islands. These regions feature extensive peatlands that become highly flammable during dry seasons. The occurrence of fires in these areas has significantly affected the environment, leading to the loss of various flora and fauna populations. In 2023 and 2024, the number of fire hotspots increased as human activities returned to pre-COVID-19 levels after several years of significant decline. Spatial mapping reinforces these findings, demonstrating that fire hotspots are primarily concentrated in the provinces of Sumatra and Kalimantan, which are known for their extensive peatlands and agricultural activities, particularly oil palm and pulpwood plantations.



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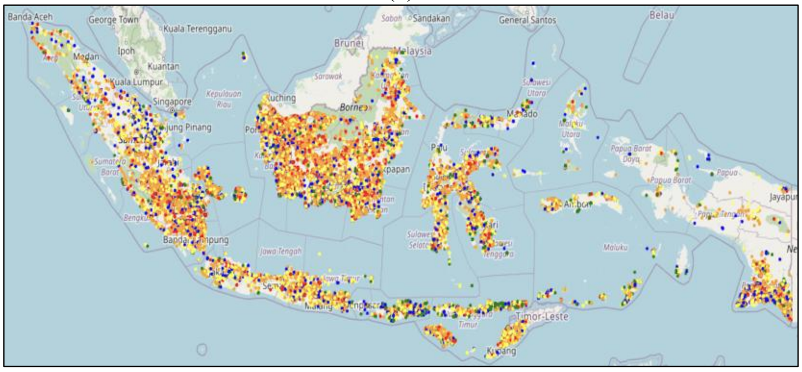

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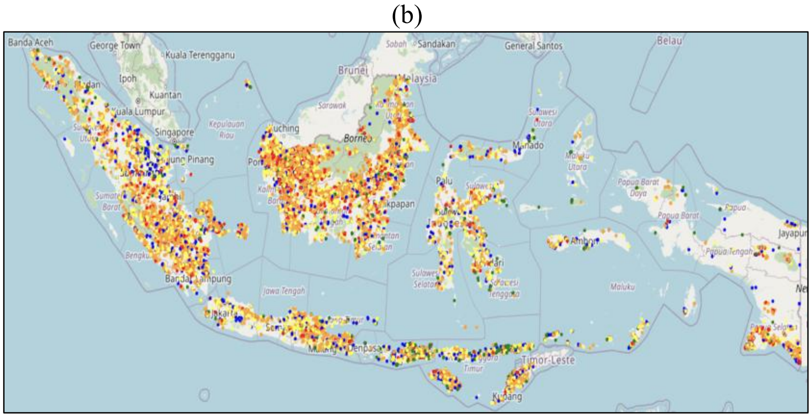
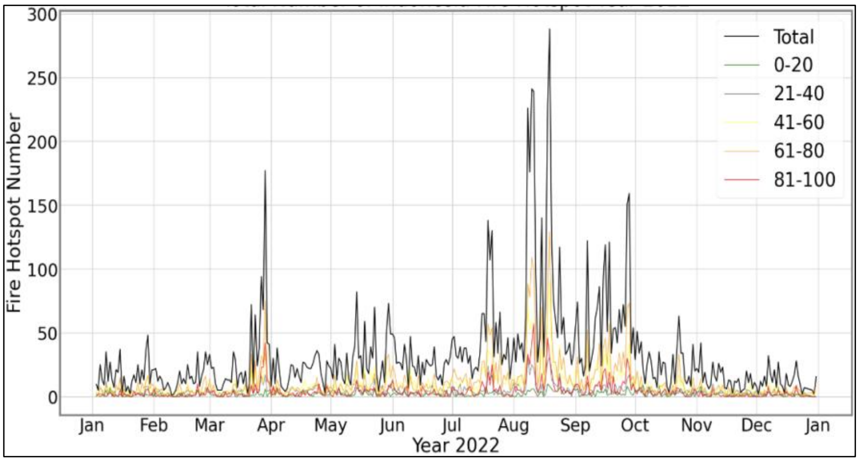


(c)

Figure 2: Fire hotspots detected in Indonesia from 2022 to 2024: (a) 2022 (b) 2023 and (c) 2024.
Source: Authors, (2026).

The maps indicate that numerous fire hotspots are located near areas undergoing land-clearing and agricultural expansion, suggesting a strong correlation between human activities and fire occurrences. In addition, the intensity graphs and maps reveal that certain regions experience recurrent fire incidents annually, highlighting their persistent vulnerability.

This underscores the necessity for more effective fire prevention strategies, including stricter enforcement of land-use regulations, improved peatland management, and community-based fire monitoring systems. The fire hotspot data were visualized using Python graphical tools to illustrate temporal trends and the spatial distribution of fire intensity. Time-series graphs were generated to depict variations in fire occurrences over specific periods, while geographic mapping techniques were employed to display the concentration and intensity of hotspots across various locations. This comprehensive analysis yielded valuable insights into the patterns and drivers of fire incidents, contributing to a better understanding of fire dynamics in the studied areas. Figure 3 shows the complete plotted data of fire hotspots chronologically from (a) 2022 to (c) 2024.



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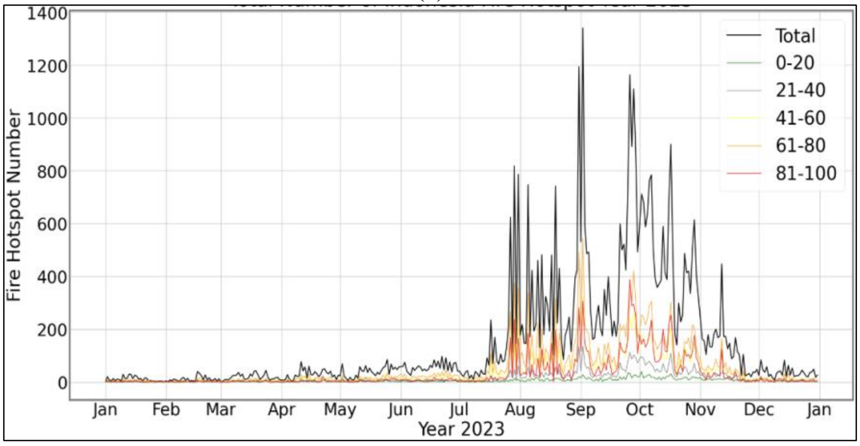

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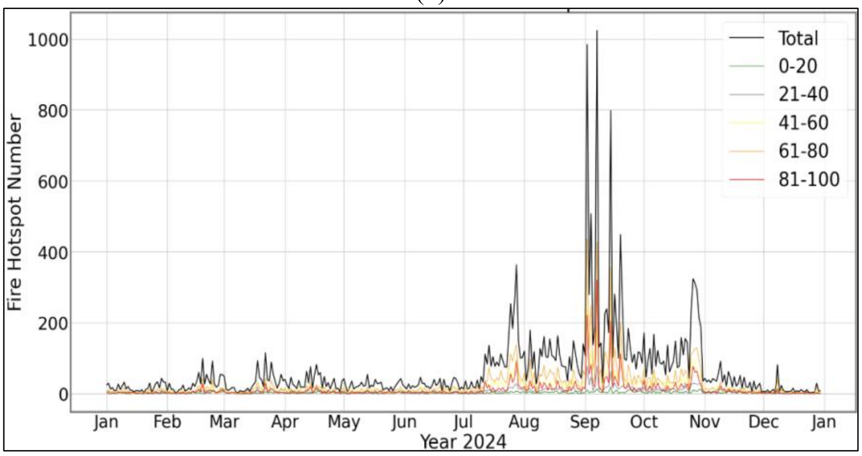

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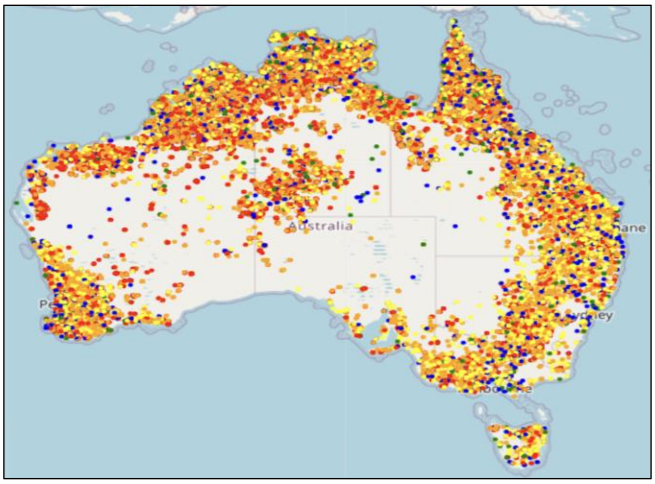
Figure 3: Fire hotspots detected in Indonesia from 2022 to 2024: (a) 2022 (b) 2023 and (e) 2024.
Source: Authors, (2026).

In contrast, Australia's fire seasons have intensified over the past few decades, highlighted by significant events such as the 2009 Black Saturday and the 2019–2020 Black Summer bushfires. NASA's analysis of Earth data indicates a marked increase in both the length and severity of fire seasons, driven by rising temperatures and prolonged droughts. Unlike in Indonesia, where fires are primarily human-induced, bushfires in Australia are primarily driven by natural sources such as lightning strikes. However, climate change and fuel accumulation have worsened their effects Fire hotspots in Australia were mapped using NASA Earth Data, illustrating the spatial distribution and intensity of fire occurrences throughout the region. Figure 4 displays this mapping of fire hotspots from 2022 to 2024.



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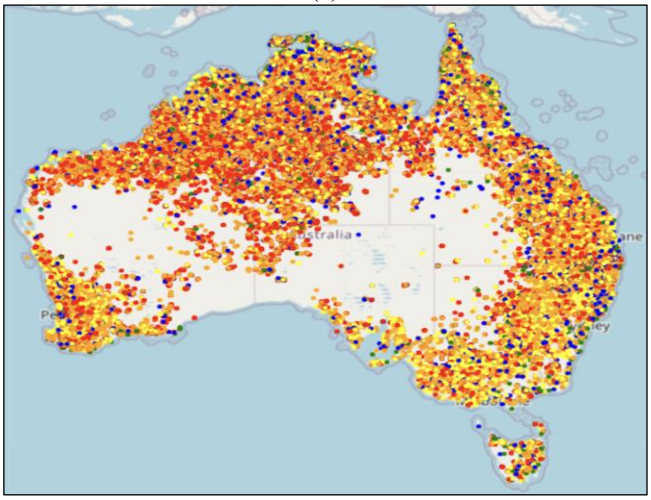

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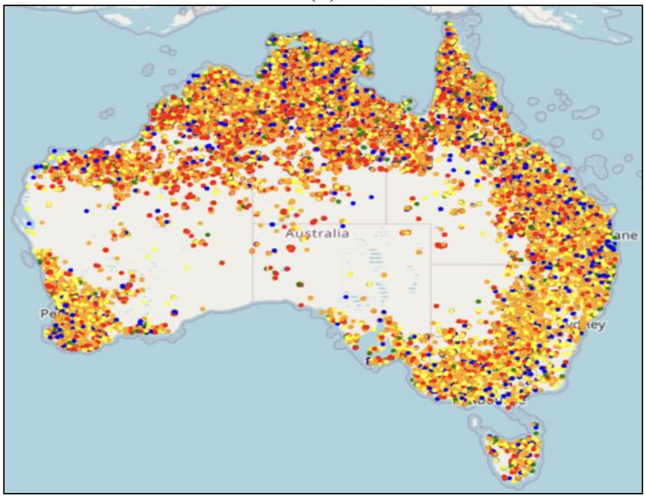
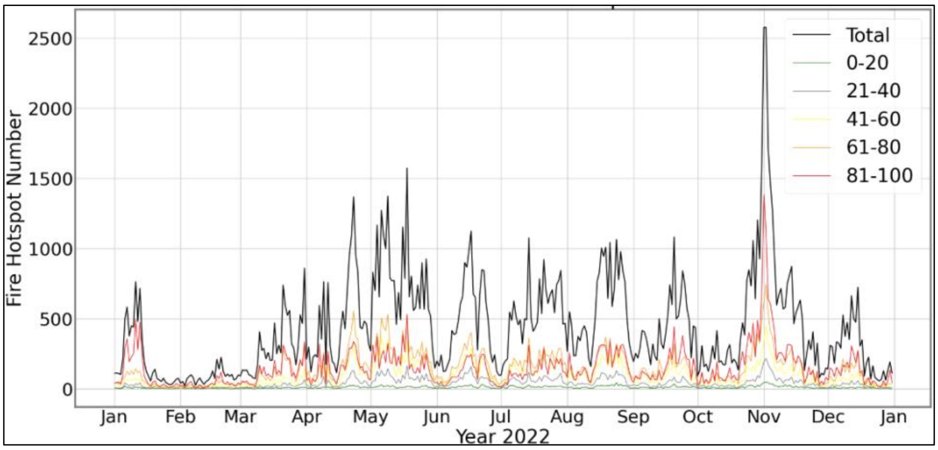


(c)

Figure 4: Results of fire mapping in Australia: (a) 2022 (b) 2023 and (c) 2024.
Source: Authors, (2026).

An analysis of fire hotspot intensity in Indonesia revealed significant temporal and spatial patterns closely linked to climatic conditions and land-use practices. Time-series graphs show that the number and intensity of fire hotspots exhibit substantial seasonal variations, with noticeable peaks occurring during the dry season, typically between August and October. This pattern correlates with the well-documented monsoon cycle in Indonesia, where extended dry periods create favourable conditions for vegetation dryness and heightened fire risk. The graphs also indicate a significant increase in fire intensity during specific years, particularly those associated with El Niño events. During intense El Niño periods, reduced rainfall and higher temperatures contribute to more severe and widespread fires. This is evident in the increased number of hotspots and higher average FRP values recorded in those years, such as 2015 and 2019, which correspond with severe haze episodes and extensive forest and peatland fires in Indonesia. Figure 5 shows the intensity of fire hotspots in Australia from 2022 to 2024.



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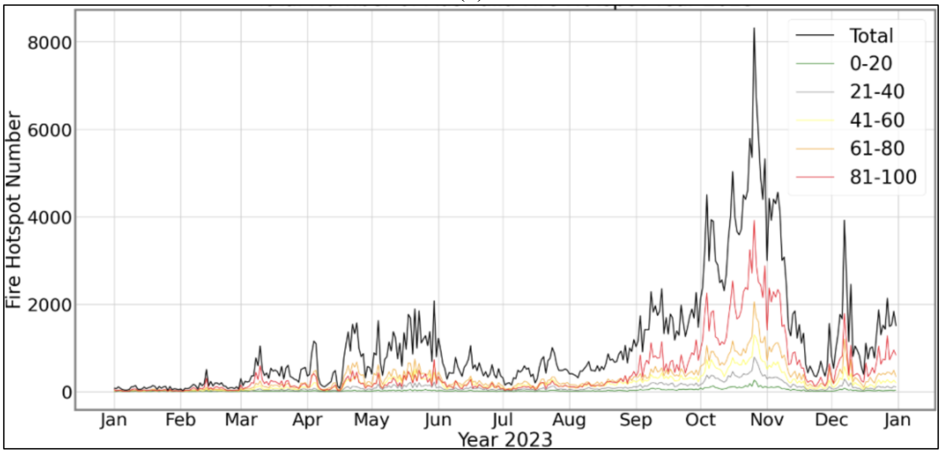

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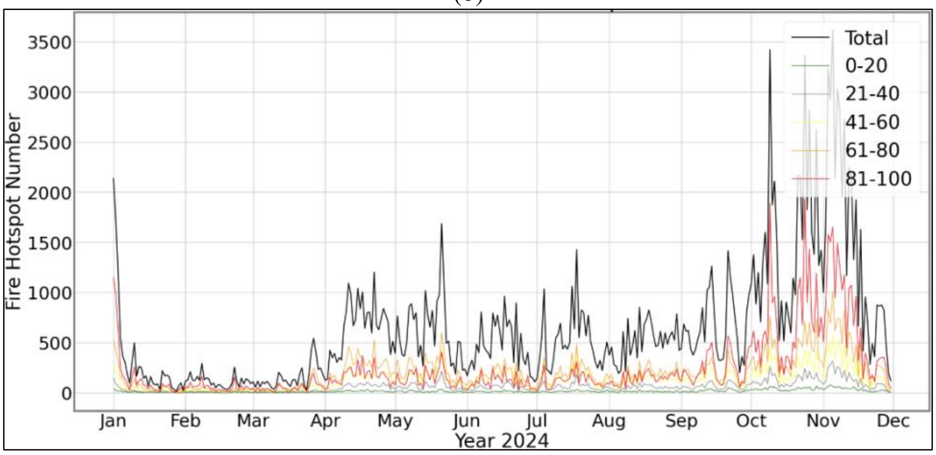

(c)

Figure 5: Fire hotspots detected in Australia from 2022 to 2024: (a) 2022 (b) 2023 and (c) 2024.
Source: Authors, (2026).

Based on an analysis of historical fire hotspot data obtained from NASA's Earth Data, particularly the FIRMS platform, predicting potential fire hotspot activity in Australia for 2025. The data reveal consistent seasonal patterns, with fire occurrences peaking during the dry and hot months, typically from September to March, particularly in regions such as the Northern Territory, Queensland, and Western Australia. Furthermore, analysis of past data shows a strong correlation between increased fire activity and climatic factors, including prolonged droughts, higher-than-average temperatures, and El Niño events. Given current climate trends and forecasts predicting elevated temperatures and reduced precipitation in parts of Australia in 2025, the intensity and frequency of fire hotspots are likely to remain high, particularly in vulnerable areas characterized by dry vegetation and significant land-use changes. Therefore, this predictive analysis highlights the im-portance of implementing proactive fire management strategies, such as early warning systems, land management policies, and community preparedness, to mitigate potential fire risks in the upcoming year. Figure 6 presents the visualized predictive model for fire risks in 2025 based on our analysed data.

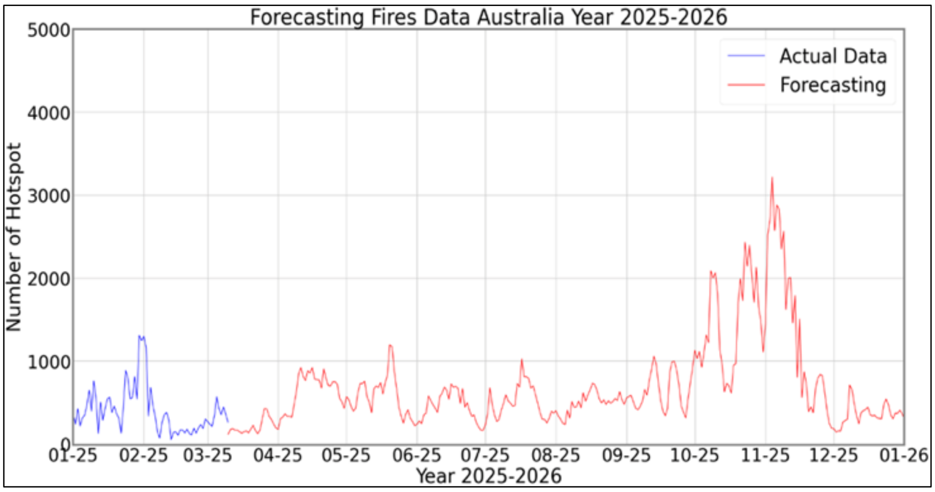

Figure 6: Forecast of the number of fire hotspots in Australia for the year 2025.
Source: Authors, (2026).

The prediction for fire hotspot occurrences in Indonesia for 2025 is informed by analysing historical data sourced from NASA Earth Data, specifically the FIRMS active fire datasets. This analysis reveals a recurring pattern of heightened fire activity during the dry season, particularly from July to October, with significant concentrations of hotspots in regions such as Sumatra and Kalimantan. Previous trends also indicate that fire intensity and frequency increase during El Niño years, contributing to prolonged drought conditions and drier peatlands and making them highly susceptible to fires. Considering climate projections and ongoing risk factors, including land-use practices such as slash-and-burn agriculture and peatland drainage, fire hotspot activity in Indonesia is expected to remain high in 2025, particularly if an El Niño event occurs. Consequently, this predictive analysis underscores the necessity for strengthened fire prevention measures, improved peatland management, and early warning systems to mitigate the potential environmental and health impacts of fires in the coming year. Figure 7 illustrates the potential for forest fires in Indonesia from September to October 2025.

Figure 7: Forecast of the number of fire hotspots in Indonesia for the year 2025.
Source: Authors, (2026).

The number of fire incidents in Indonesia, as illustrated in Figure 5, shows a significant accumulation from August to December each year, peaking in September and October. By contrast, Figure 7 highlights the trend of fire incidents in Australia hotspots from 2021 to 2024, which accumulated from March to November. Notably, the year 2020 experienced unusually low incidents due to the COVID-19 pandemic. Forest fires in both countries have resulted in significant environmental harm. In Indonesia, peatland fires release vast quantities of carbon, exacerbating global climate change. In addition, bio-diversity loss, habitat destruction, and soil degradation are critical concerns.

Similarly, Australian bushfires have had devastating effects on ecosystems, with the 2019–2020 Black Summer fires resulting in the loss of nearly three billion animals and endangering many species. Both Indonesia and Australia have also faced significant economic losses due to forest fires. In Indonesia, the haze crisis disrupts transportation, affects tourism, and contributes to respiratory illnesses, with financial costs estimated at $16 billion during the 2015 fire season alone. In Australia, bushfires have destroyed homes, infrastructure, and agricultural land, with the Black Summer fires leading to an estimated $110 billion in damage.

The health impacts from these fires, including respiratory diseases and mental health issues, have been widely reported in both countries due to prolonged exposure to smoke pollution. The effectiveness of Indonesia’s fire management approaches relies on various mitigation strategies, including regulatory measures such as the moratorium on peatland development and stricter land-clearing regulations. However, enforcement remains weak due to corruption and a lack of resources. Community-based fire prevention initiatives, which involve local communities in fire prevention and sustainable agriculture, have demonstrated some success in reducing fire incidents.

Moreover, technological solutions, such as satellite monitoring and IoT-based early warning systems, have been utilized to detect and prevent fire outbreaks. Despite these efforts, challenges, such as illegal land-clearing and conflicting economic interests, continue to impede effective fire management. By contrast, Australia has implemented a combination of traditional and modern fire mitigation strategies. Controlled burns, through prescribed burning, aim to reduce fuel loads, but their effectiveness is limited in extreme weather conditions. Policies promoting fire-resistant infrastructure encourage the use of fire-resistant building designs and urban planning in fire-prone areas.

Recognition of Indigenous fire knowledge has increased, with a focus on employing low intensity burns to prevent large-scale fires. Australia also has a well-established fire response system in place. However, the growing severity of fires due to climate change necessitates continuous adaptation and improvements in fire management strategies. A comparative analysis reveals key lessons from each country's experience, emphasizing the importance of more vigorous policy enforcement. Indonesia could benefit from Australia's strict fire management policies and advanced response systems.

In addition, the integration of traditional Indigenous fire management practices from Australia could be adapted in Indonesia, particularly within community-based fire prevention programs. Both countries can also harness technological innovations, such as advancements in satellite monitoring, AI-driven fire prediction models, and IoT-based early warning systems. Future research should focus on developing cross-border cooperation for haze reduction in Southeast Asia, exploring climate adaptation strategies for bush-fire-prone regions, enhancing community involvement in fire prevention programs, and investing in AI-driven fire-risk assessment models.

V. CONCLUSIONS

The analysis of forest fire trends in Indonesia and Australia highlights the increasing threat posed by climate change and land-use practices. Although both countries have implemented various mitigation strategies, they continue to face challenges in policy enforcement, community engagement, and technological integration. The graph results reveal that seasonal climatic factors and human activities contribute to the intensity of fire hotspots in Indonesia. These visualizations offer valuable insights into the timing and locations where fires are most likely to occur, providing essential information for policymakers, environmental agencies, and disaster management authorities to formulate targeted mitigation efforts.

Learning from past experiences and adopting innovative solutions will be critical in reducing the frequency and effects of future fire events. The literature indicates that, although Indonesia and Australia face unique fire challenges, valuable lessons can be learned from each country's experiences. Effective fire management requires a combination of policy enforcement, technological advancements, community engagement, and international cooperation. As climate change amplifies fire risks, future research should focus on integrating scientific innovations with traditional fire management practices to develop more sustainable and adaptive mitigation strategies.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Evizal Abdul Kadir.
Methodology: Hitoshi Irie.
Investigation: Sri Listia Rosa.
Discussion of results: Wan Aezwani Wan Abu Bakar.
Writing – Original Draft: Evizal Abdul Kadir and Sri Listia Rosa.
Writing – Review and Editing: Hitoshi Irie.
Resources: Evizal Abdul Kadir and Aezwani Wan Abu Bakar.
Supervision: Hitoshi Irie.
Approval of the final text: Hitoshi Irie and Evizal Abdul Kadir.

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