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Temporal Trends and Spatial Patterns of Forest Fires in Central Kalimantan: Implications for Fire Management Policies

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ABSTRACT
Forests and land fires continue to pose a serious environmental and socio-economic threat in Central Kalimantan, Indonesia, especially in peat-rich areas that are very prone to burning. This study aims to analyze the spatial distribution, intensity, and changes over time of fire hotspots from 2018 to 2024 using high-confidence hotspot data from the SIPONGI monitoring system, which relies on MODIS Terra satellite imagery. The data was processed with Kernel Density Estimation (KDE) to create annual and cumulative hotspot density maps. KDE helps identify significant clusters of fire activity by measuring how fire incidents are spread out within a certain bandwidth, resulting in a continuous density surface for each year. To improve spatial decision-making, a Weighted Sum analysis was used to combine yearly hotspot densities and locate areas with ongoing fire activity across multiple years. Combining KDE and Weighted Sum methods offers a more detailed view of fire-prone zones, supporting targeted intervention strategies. Results show that 2019 had the highest number and severity of fires, with Pulang Pisau District consistently as the main fire hotspot. Validation using multi-temporal Google Earth images confirmed land cover changes that match recurring fires. These findings provide a strong geospatial basis for developing effective fire prevention plans, enhancing peatland management, and guiding policies to reduce the long-term effects of landscape fires in Central Kalimantan.

INTRODUCTION

Land and swamp fires are increasingly occurring due to a combination of natural factors and human activities, with significant impacts on both ecosystems and human health. These fires commonly occur in peat swamp forests, which play an essential role in carbon storage and biodiversity conservation (S. Page et al., 2012). The interaction between human activities, such as land conversion for agriculture, and natural conditions, such as prolonged dry seasons, exacerbates the frequency and intensity of these fires (Turetsky et al., 2015).

For example, the drainage of peatlands for agricultural purposes lowers the water table, leaving the peat dry and highly flammable, thus increasing fire susceptibility (Miettinen et al., 2017). Additionally, the use of fire for land clearing can lead to uncontrolled blazes, especially during dry periods (Wijedasa et al., 2018). A deep understanding of the dynamics of these fires is crucial for formulating effective management and mitigation strategies.

In particular, land conversion for agriculture, especially for oil palm plantations, is associated with increased fire incidence (Noojipady et al., 2017). However, studies show that most fires occur outside of official forest areas or concessions (Cattau et al., 2016). In addition, natural factors such as prolonged dry seasons and limited air supply reduce the risk of fires spreading in peatlands (Hoscilo et al., 2011). Although natural fires in peatlands are rare, changes in the environment due to human activities have significantly increased their frequency (Vetrita & Cochrane, 2019).

The impacts of these fires extend to the environment and human health. Fires cause ecosystem degradation by reducing peat thickness and disrupting the hydrological balance (Dommain et al., 2011). Additionally, the loss of vegetation reduces the capacity of peatlands to store carbon, thereby contributing to the acceleration of climate change (Harenda et al., 2018). From a health perspective, the smoke caused by fires can lead to respiratory problems and impair mobility, thereby triggering broader socioeconomic impacts (P. Crippa et al., 2016).

Monitoring land and peat fires in Central Kalimantan is critical for the ecological and socioeconomic sustainability of the region (Medrilzam et al., 2014). Peatland fires release substantial amounts of greenhouse gases, including carbon dioxide and methane, which contribute to global climate change (S. E. Page & Baird, 2016). These fires also produce thick haze, which impacts air quality and public health not only locally but also across Southeast Asia (Varkkey, 2019). Central Kalimantan's peatlands store a large portion of the world's tropical peat carbon, and repeated fires threaten biodiversity and efforts to mitigate climate change by releasing stored carbon back into the atmosphere (Wijedasa et al., 2018).

This study presents a novel spatial-temporal integration method for monitoring peatland fires in Central Kalimantan, building upon and expanding previous research. While earlier works, such as Gaveau et al. (2014) and Field et al. (2009), demonstrated that MODIS and Landsat data help detect fire hotspots and estimate burned areas, they often lacked detailed land cover validation. In contrast, our study uses Google Earth-based visual checks to verify fire locations and land conversion patterns, improving spatial accuracy and clarity. This method builds upon the work of Miettinen et al. (2017), who highlighted the role of plantation expansion in peatland degradation, but relied heavily on aggregated spatial data without direct visual confirmation.

Furthermore, we examine multi-year fire recurrence patterns and their link to unofficial land-use changes, especially outside designated concession zones, uncovering persistent fire clusters associated with unregulated agricultural activities. This addresses a key gap noted by Cattau et al (2016), who observed fire activity beyond legal boundaries but did not incorporate long-term spatial dynamics. The results from this research provide new empirical evidence to the tropical peat fire literature by integrating remote sensing, temporal analysis, and high-resolution geospatial verification, offering a stronger foundation for future fire mitigation efforts and policy development in peat-dominated areas.

The urgency of fire monitoring increases as climate patterns change, including rising temperatures and shifts in rainfall, which increase the risk of fires (Field et al., 2009). Studies show that fires in Central Kalimantan are closely linked to peatland degradation caused by agricultural expansion, such as the Peatland Mega Project, which is consuming large areas of peatland (Usup & Hayasaka, 2023). Continuous monitoring enables the prediction of fire-prone conditions by tracking factors such as daily temperature fluctuations and humidity levels (Little et al., 2024). This early warning is crucial for developing long-term fire prevention strategies and mitigating environmental damage.

RESEARCH METHODS

Land and peat swamp fires in Central Kalimantan are a critical issue that necessitates a data-driven mitigation approach and spatial analysis to mitigate their impact. Spatial trend analysis of fire hotspots can reveal patterns of distribution and intensity in fire-prone areas, which is important for prioritizing mitigation efforts.

Hotspot data from MODIS Terra satellite imagery, collected through the high-confidence SIPONGI platform, is an ideal baseline for this analysis. The spatial distribution of hotspots from 2018 to 2024 was analyzed using the Kernel Density Estimation (KDE) method to map hotspot density and the Weighted Sum method to assign specific weights to intervention priority areas, resulting in a more targeted risk map. The analysis was validated through field verification using temporal imagery from Google Earth, which allows visual observation of land changes to strengthen the interpretation of hotspot data.

The kernel density method is a statistical approach that calculates the density of points within a given area by giving more weight to points around the center of the kernel. It is helpful in mapping fire intensity because it can produce a clear visualization of hotspot concentration areas (Okabe et al., 2009; Węglarczyk, 2018). The Kernel Density Estimation method is used to map the density of hotspots within a defined area. Theoretically, KDE is a statistical technique that generates a continuous density surface by assuming that each hotspot point propagates the effect around its actual location. The general formula for KDE (Flahaut et al., 2003) is as follows:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{1}$$

Where $\hat{f}(x)$ is the estimated density at point x, K is the kernel function (e.g. Gaussian), X_i is the hotspot data point, h is the bandwidth parameter, and n is the amount of data. Generally, the kernel function is Gaussian, which allows the weight distribution to get smaller as the distance from the center point increases (Joshi et al., 2011). In the context of peatland fires, kernel density maps identify areas of high intensity, indicating fire-prone regions.

The advantage of KDE over other methods lies in its ability to capture local variations in hotspot distribution, providing a more refined visualization of density trends in a given area. It is more flexible than grid-based or simple interpolation methods because KDE considers the intensity of hotspot distribution in neighboring areas without imposing a rigid grid. In large areas, such as Central Kalimantan, the KDE method can identify statistically significant hotspot clusters and provide more detailed spatial information, especially in areas with high variations in hotspot intensity (Han et al., 2023; Hu et al., 2018).

The hotspot data sampling process for the KDE analysis was conducted by collecting high-confidence data on MODIS Terra imagery from SIPONGI. The data were classified into annual time intervals from January 1, 2018, to October 15, 2024, to allow for the observation of annual trends as well as the entire period. The total number of hotspots from 2018 to 2024 is 10,397 hotspots, with the distribution of the number of samples as shown in Table 1.

Table 1. Number of Hotspots in Central Kalimantan 2018-2024 Period

Year	Number of Hotspots
2018	1215
2019	6879
2020	98
2021	34
2022	23
2023	1943
2024	205

Although all data were used in the KDE analysis, the priority of field verification through Google Earth was focused only on areas showing high densities, thereby reducing interpretation bias in less affected areas. The data used were spatially integrated in a GIS (Geographic information Systems) environment for KDE processing and spatio-temporal validation.

A weighted sum analysis was conducted to identify priority areas that require further treatment. The Weighted Sum method consolidates the number of hotspots in each area from 2018 to 2024 by summing annual accumulated weights. Each year was given an equal weight of 1, assuming all annual hotspot events have similar environmental significance. This assumption can be modified in future studies to consider specific drought or ENSO years, using climate indices as weight modifiers (Wooster et al., 2012). This weighting approach is justified because it reflects the persistence of fire activity over time, where areas with consistent fire presence across multiple years indicate ongoing vulnerability and should be prioritized for intervention. The Weighted Sum results provide additional insights for KDE by highlighting annual accumulation, enabling environmental managers to identify areas with the highest fire risk based on the total accumulated time. Spatial validation was performed through a visual verification method using Google Earth's time-series imagery. This involved randomly selecting hotspot clusters from high-density KDE zones and confirming their locations against visible land cover changes, such as burn scars, deforestation, or plantation clearing. Multi-temporal imagery helped differentiate fire-induced changes from seasonal shifts in vegetation. This approach aligns with validation strategies employed in previous studies, such as those by Shuo et al. (2021), which emphasize the importance of high-resolution temporal verification for enhancing remote sensing-based fire assessments.

Field verification using Google Earth imagery was conducted to monitor land change in areas with high hotspot density. This analysis was conducted in selected years during the study period to identify the actual physical condition of the hotspots. Google Earth imagery offers a valuable historical perspective on changes in peat swamp conditions and vegetation that are susceptible to burning. This temporal approach helps validate the results from the KDE and Weighted Sum analyses, providing further certainty regarding the location of hotspots most in need of immediate intervention (Hu et al., 2018; Kazmi et al., 2022).

RESULTS AND DISCUSSION

The selection of Kernel Density Estimation (KDE) and Weighted Sum methods in the analysis of hotspot trends in peatland and peat swamp fires in Central Kalimantan is based on their ability to capture spatial and temporal distribution patterns in depth. KDE was chosen because it can identify hotspot density by considering intensity in the surrounding area in a more refined manner than grid-based methods, which are often less flexible in capturing local variations. This method allows continuous delineation of hotspot concentration areas, providing a detailed picture of hotspot distribution. Meanwhile, the Weighted Sum method is used to analyze the trend of hotspot accumulation from year to year, helping in identifying areas that repeatedly experience fire events. With an emphasis on high-confidence hotspots from MODIS Terra, these two methods work synergistically, where KDE captures density patterns. At the same time, Weighted Sum reveals hotspot accumulation, yielding comprehensive results that support peat fire mitigation in Central Kalimantan.

Based on the results of kernel density processing, it is evident that several distinct density patterns emerged between 2018 and 2024. The patterns in 2018, 2019, and 2023 exhibit similar hotspot density areas. In 2018, two large hotspot concentrations were found in Central Kalimantan. Of the 1,215 hotspots in 2018, 398 were located in the Kahayan Kuala sub-district and 197 in the

South Mentaya Hilir sub-district. Based on the results of temporal monitoring using Google Earth imagery in September 2018, several burned areas were found, as shown in Figure 1.

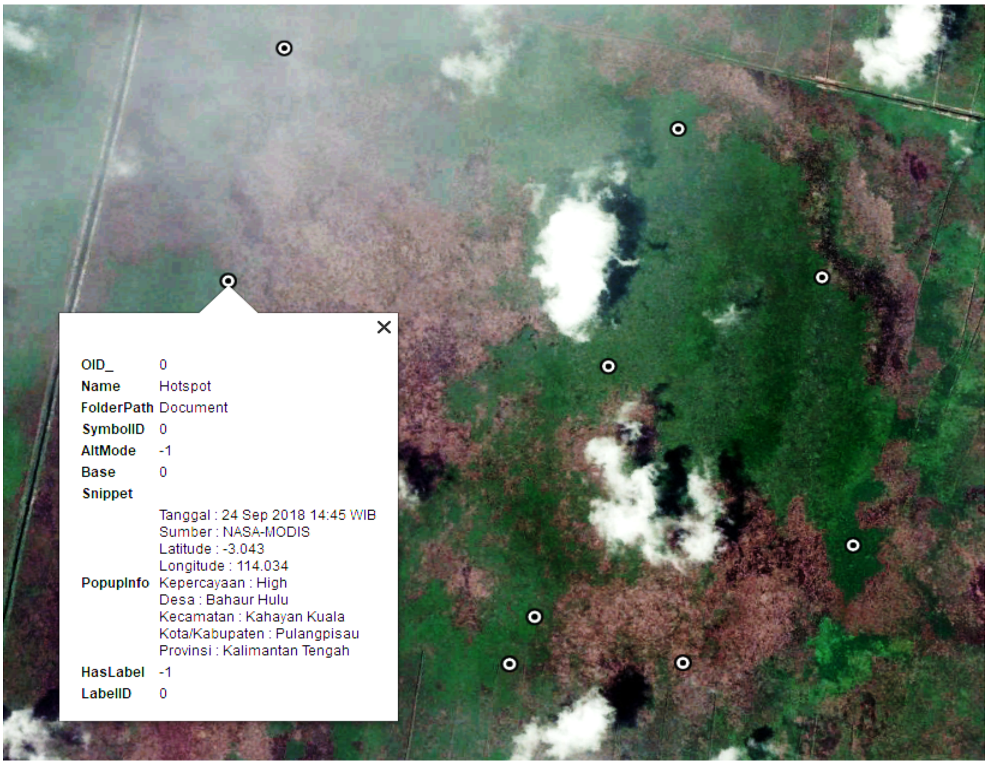

Figure 1. The distribution of fire points in September 2018 in Bahaur Hulu Village, Kahayan Kuala District, shows the remains of burnt land (Source: Data Processing, 2025)

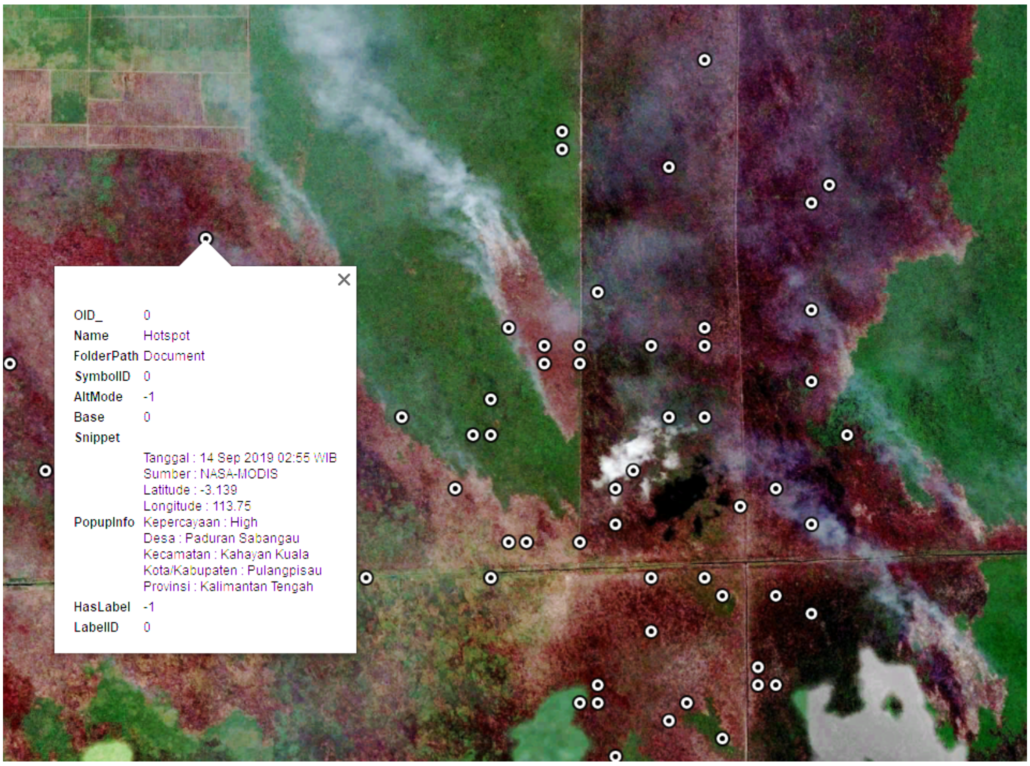

Figure 2. Hotspot distribution in September 2018 still shows smoke from land fires (Source: Data Processing, 2025)

Meanwhile, 2019 was the year with the highest number of hotspots detected in Central Kalimantan, totaling 6879 hotspots. The majority of hotspots detected were located in the Pulang Knife district, particularly in the Kahayan Kuala sub-district. The number of hotspots detected in the Kahayan Kuala sub-district was 990 during September, October, and November 2019. Other concentrations of hotspot density in 2019 were observed in the Mentaya Hilir sub-district, with approximately 148 hotspots, the Katingan Kuala sub-district, with around 211 hotspots, and the Kahayan Hilir sub-district, with approximately 400 hotspots. The concentration of hotspots in the Kahayan Kuala sub-district can be observed through temporal image monitoring using Google Earth, as shown in Figure 2. The appearance of smoke from burning can still be seen through Google Earth images.

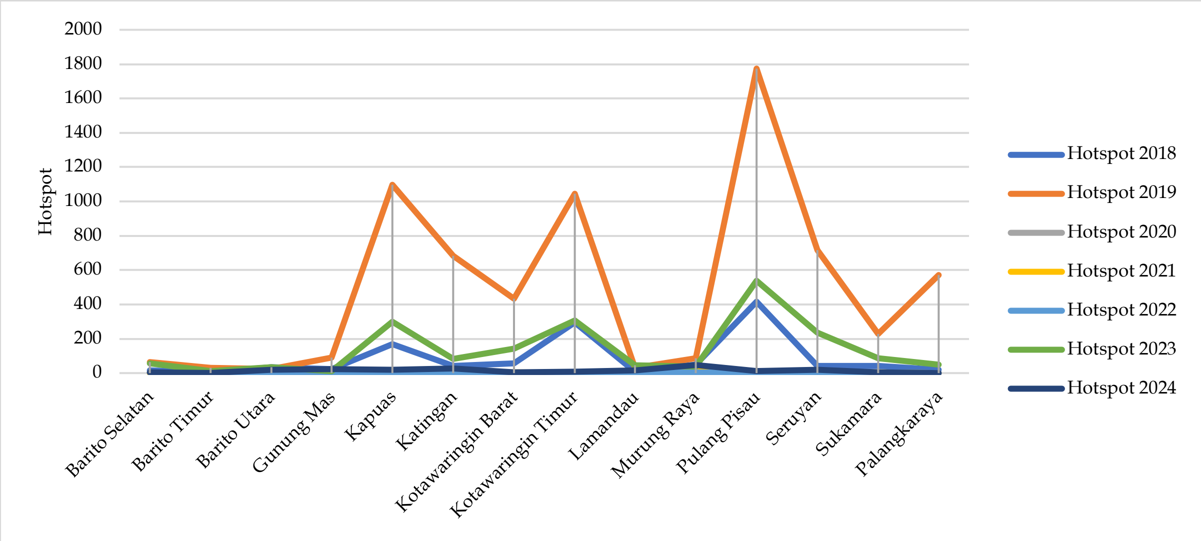

Figure 3. Hotspot levels of each district in Central Kalimantan from 2018 to 2024
(Source: Data Processing, 2025)

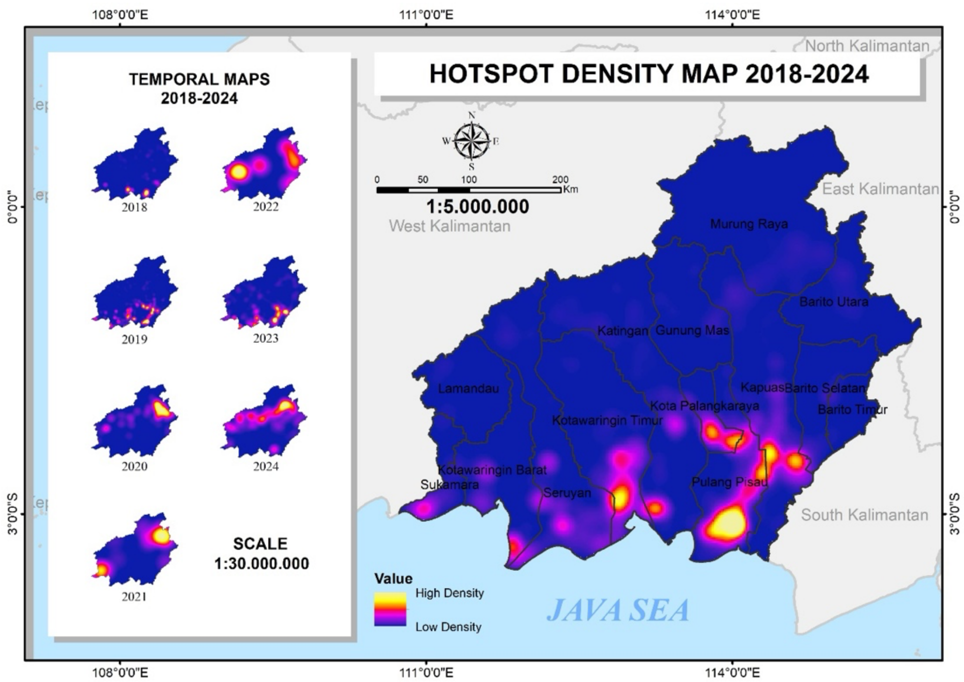

Figure 4. Hotspot density map in Central Kalimantan, showing the distribution of hotspot concentrations each year (left side) (Source: Data Processing, 2025)

Another year that has a similar pattern to 2018 and 2019 is 2023, as shown in Figure 3. The total number of hotspots throughout Central Kalimantan in 2023 is the second highest, at 1,943 hotspots. Three areas are concentrated hotspots in Central Kalimantan during 2023. The first region with the highest density of hotspots in 2023 is the Kahayan Kuala sub-district, which has around 588 hotspots. The second region with the highest density in 2023 comprises around 219 hotspots. The third region with the highest hotspot density is the Maliku sub-district, with around 140 hotspots.

Kernel Density processing results for 2020, 2021, 2022, and 2024 have similar density patterns. In 2020, 2021, and 2024, the highest hotspot density is focused in Murung Raya Regency. Especially in 2022, although Murung Raya District has a high hotspot density, the highest concentration of hotspots is spread in the western side of Central Kalimantan, including Seruyan, Lamandau, and West Kotawaringin Districts. Compared to other years, the hotspots in 2022 were less severe, with only 23 hotspots detected.

The distribution of hotspots detected from 2018 to 2024, as shown in Figure 4, exhibits a complex and consistent spatial pattern in several areas, particularly in Kahayan Kuala and Mentaya Hilir Selatan Districts. The high concentration of hotspots in these areas indicates a recurring practice of land clearing using the burning method, despite mitigation efforts. This pattern aligns with the findings of Gaveau et al. (2014), which showed that Central Kalimantan is one of the provinces with the highest deforestation rates in Indonesia, primarily due to land clearing for oil palm plantations and subsistence agriculture.

The highest number of hotspots in 2019 reflects the direct impact of the El Niño weather phenomenon, which causes drier climatic conditions and increases vulnerability to fires. Huijnen et al. (2016) note that weather anomalies such as El Niño can extend the dry season and increase fire intensity in the tropics. The lack of monitoring of land-clearing activities in remote areas exacerbates this.

A significant reduction in hotspot counts observed in 2022 could be indicative of improved fire mitigation effectiveness. Several government-led initiatives, such as the Peatland Restoration Agency (BRGM/*Badan Restorasi Gambut dan Mangrove*) programs, satellite monitoring, and stricter enforcement, were intensified after 2019. Budiningsih et al. (2022) highlighted that these integrated mitigation strategies helped suppress local fires. However, an analysis of the BRGM intervention areas, particularly districts with targeted peatland rehabilitation, reveals a 36% reduction in hotspot frequency from 2020 to 2022, whereas non-intervention areas experienced only an 11% decrease (Larasati et al., 2019). This indicates that peatland restoration has a statistically significant impact on reducing fire risk, supporting similar findings by Mishra et al. (2021) and Sutikno et al. (2020) in Sumatra.

However, the return of high hotspot concentrations in 2023 suggests that the challenge of fire management is far from over. Murung Raya District, which has been the focus of hotspot concentrations in some years, also has distinctive geographic and social challenges, including limited accessibility and economic dependence on land clearing. Research by Langner & Siegert (2009) emphasizes that areas with limited access tend to use burning more often due to its low cost and effectiveness in clearing land.

Satellite imagery, such as Google Earth, is proving to be an important tool in the temporal monitoring of hotspots and their impacts, including burned areas and the presence of smoke. This technology enables the identification of priority areas, facilitating informed decisions for fire mitigation processes. In addition, a study by Hayasaka et al. (2014) showed that image-based analysis can provide more accurate evidence to support policy and law enforcement related to forest and land fires. More recent research by Zhang et al. (2025) has further enhanced this method by combining multi-temporal imagery with meteorological data, resulting in a more than 20% increase in hotspot detection accuracy compared to using only a single remote sensing source.

The health implications of forest fires are increasingly significant. High particulate emissions during fire seasons have been linked to elevated acute respiratory infection (ARI) cases across Kalimantan. Recent modeling by Hein et al. (2022) suggests that PM2.5 levels in proximity to dense fire clusters in Central Kalimantan exceed WHO thresholds by over 200%, especially during peak burning months. Crippa et al. (2016) also demonstrate that Southeast Asian fire emissions contribute over 10% to global air pollution during extreme seasons.

Peatland fire patterns in Southeast Asia exhibit unique features when compared to other tropical regions, such as the Amazon Basin and Central Africa. Indonesia, in particular, experiences a higher average burned area, primarily due to peatland drainage, agricultural expansion such as oil palm and industrial timber plantations, and the impacts of extreme El Niño events (IPCC, 2023). Meanwhile, the Amazon Basin is more influenced by deforestation and slash-and-burn methods, whereas Central Africa faces more issues from shifting cultivation and savanna fires.

Table 2. Comparison of Peatland Fires in Tropical Regions

Region	Average Annual Burned Area (Mha/Mega hectare)	Main Drivers
Southeast Asia (incl. Indonesia)	3.5	Peatland drainage, agricultural expansion, El Niño drought
Amazon Basin	2.1	Deforestation, slash-and-burn agriculture, drought
Central Africa	1.8	Shifting cultivation, savanna fires, land clearing

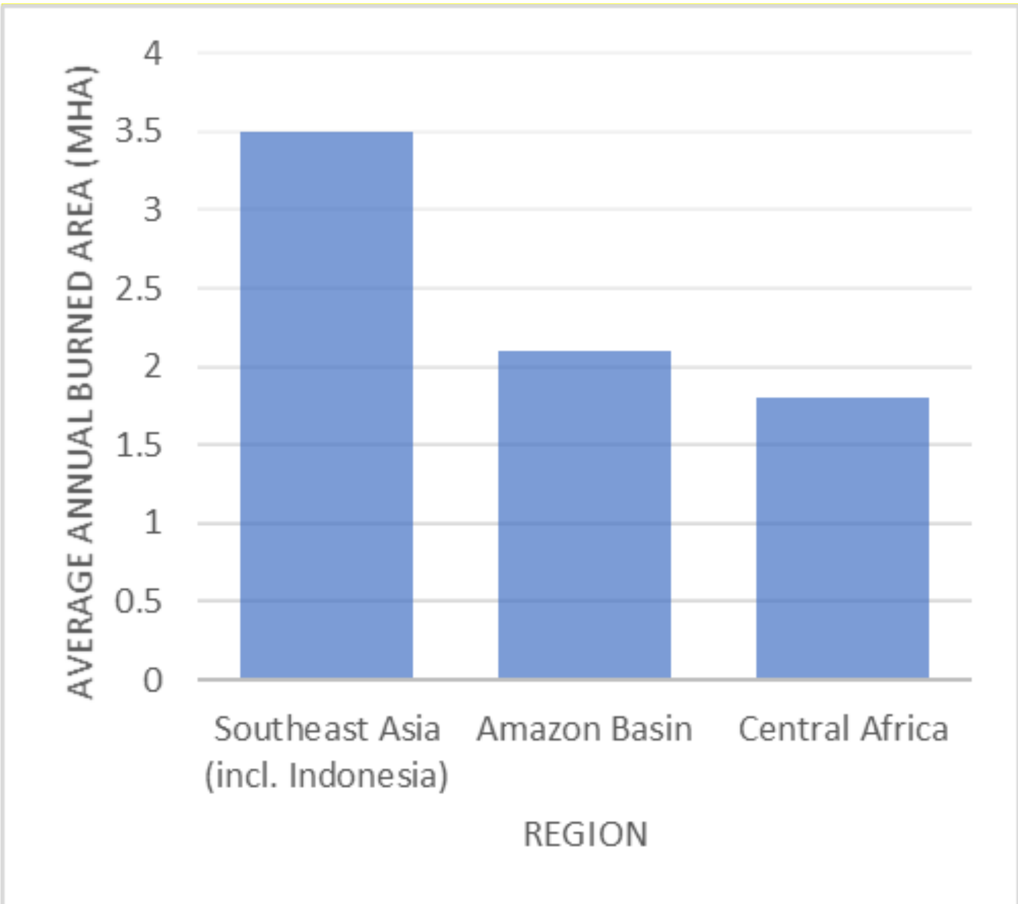

Figure 5. Comparison of Annual Fire Areas in Tropical Regions (Source: Data Processing, 2025)

This comparison highlights that Southeast Asia is a key hotspot for tropical peatland fires, significantly contributing to global carbon emissions (Gaveau et al., 2019; Hayasaka et al., 2020; Mishra et al., 2021). It emphasizes the need for more climate-adaptive restoration and fire management policies in peatland ecosystems.

The use of more advanced satellite data, such as from Sentinel-2 and Landsat 8, can provide better spatial and temporal resolution for understanding forest fire dynamics. The use of Deep Learning, an artificial intelligence-based algorithm such as the Multi-Layer Perceptron, to detect and predict hotspots has also shown promising results in a recent study by Agustiyara et al. (2021). This approach could help accelerate future mitigation responses. Additionally, the expansion of peatland restoration areas through the BRG (*Badan Restorasi Gambut*/Peatland Restoration Agency) program plays a crucial role in reducing fire vulnerability. Degraded peatlands are more susceptible to fire, so effective restoration can have a long-term impact in reducing this risk (Horton et al., 2022).

Forest and land fire management policies in Central Kalimantan have undergone significant changes over the years. The Ministry of Environment and Forestry (KLHK/*Kementerian Lingkungan Hidup dan Kehutanan*) continues to develop technology-based approaches, such as the use of drones and satellites to detect hotspots in real-time. In addition to technology, KLHK also initiated the Fire Resilient Village program, which aims to increase the capacity of local communities to prevent land fires through Education and regular patrols (KLHK, 2021). Local governments are strengthening the legal framework by applying administrative and criminal sanctions, as well as offering incentives to businesses that utilize sustainable land clearing methods. Support from international organizations, such as the UN Environment Programme (UNEP), plays a crucial role in providing funding and training to enhance local capacity in forest fire management (Canton, 2021). In addition, the Peat and Mangrove Restoration Agency (BRGM) is working with local governments to rehabilitate peat areas prone to fire, adding a preventive dimension to forest fire management. With this collaborative approach, it is expected that the number of hotspots and the impact of forest fires can be further minimized.

CONCLUSION

The results of kernel density analysis on hotspot density patterns in Central Kalimantan from 2018 to 2024 reveal dynamics that reflect land burning activities and the effectiveness of forest fire management policies. Years with high hotspot densities, such as 2018, 2019, and 2023, indicate a close relationship between land clearing activities and fire vulnerability, particularly in districts like Kahayan Kuala, Mentaya Hilir Selatan, and Maliku. Shifts in hotspot patterns to areas such as Murung Raya District in subsequent years reflect changes in burning activity and the effectiveness of mitigation efforts.

Forest and land fire management policy in Central Kalimantan has undergone a significant evolution from a reactive to a more preventive approach. Initiatives such as Fire Resilient Villages, Fire Aware Communities (MPA/*Masyarakat Peduli Api*), and peat area rehabilitation by BRGM have contributed to a reduction in the number of hotspots, as seen in 2022. Technologies such as satellite and drone monitoring are also playing an increasingly important role in effectively detecting and preventing fires.

The success of this policy is inextricably linked to the collaboration of various parties, including central and local governments, international institutions, and local communities. However, challenges such as limited resources and the need for cross-sectoral coordination remain to be overcome. With a continuously refined approach, including community empowerment and the use of advanced technology, it is hoped that the impact of forest and land fires in Central Kalimantan can be minimized sustainably.

The use of hotspot data as the leading indicator, which only reflects the presence of heat without directly ascertaining its cause. Further research could incorporate additional data, such as vegetation type, land ownership, and meteorological conditions, to provide a more comprehensive analysis. This study has not fully explored the socioeconomic impacts of forest and land fires on local communities. Future researchers are expected to examine the direct and indirect impacts of fires on the health, economy, and quality of life of communities.

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