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Research Article

Spatiotemporal Patterns of Burned Areas Based on the Geographic Information System for Fire Risk Monitoring

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Forest and land fires occur every year in Indonesia. Efforts to handle forest and land fires have not been optimal because fires occur in too many places with unclear patterns and densities. The study analyzed the spatiotemporal patterns of burned areas and fire density in fire-prone areas in Indonesia. Data of burned areas were taken from http://sipongi.menlhk.go.id/. The website collected its data from NOAA (National Oceanic and Atmospheric Administration) images. Data were analyzed using the hot spot analysis to determine the spatiotemporal patterns of the burned areas and the kernel density analysis to examine the density of land fires. Findings showed that the spatiotemporal pattern from 2016 to 2019 formed a hot spot value in the peatland area with a confidence level of 90–99%, meaning that land fires were clustered in that area. In addition, the highest density of land fires also occurred in the peatland areas. Clustered burned areas with high fire density were found in areas with low–medium vegetation density—they were the peatland areas. The peatland areas must become the priority to prevent and handle forest and land fires to reduce fire risks.

1. Introduction

Forest and land fires are recurring events in Indonesia and are the main contributors to climate change [1–3]. Various methods have been carried out to overcome forest and land fires, yet they do not show satisfying results [4]. The traditional method to monitor fires employing the community is still practiced in Indonesia, including in South Kalimantan [5, 6]. This method, however, has made fire management less effective and dangerous. Electronic and computer technology has enabled the development of methods for handling forest and land fires through computer-based geospatial systems [6].

Geospatial technology is the most appropriate and easier method in analyzing geographical phenomena, including monitoring land fires [7]. As fires often occur in spatially vast and dangerous areas, the use of geospatial technology is considered the most appropriate choice to handle such fires [8]. Geospatial technology allows analyzing forest and land fires at various spatial and temporal scales [9]. Geospatial analysis can also prevent future fires and help conserve forest and land resources [10]. A geographic information system (GIS) enables efficient analysis of geographic phenomena, including spatial pattern analysis or spatial relationship modeling [9, 11–14].

Spatial autocorrelation analysis is an analysis in GIS. Spatiotemporal autocorrelation refers to the correlation of events within themselves over space and through time. It reflects the extent to which events with similar properties are clustered or dispersed [15, 16]. Spatial autocorrelation analysis aims to analyze whether the variables are spatially correlated and how relevant they are and how they generate hot spots [17, 18]. Hot spot analysis, an autocorrelation analysis, refers to calculating the Getis–Ord G_i^* statistic for each element in the dataset. The Getis–Ord G_i^* value can be used to detect the spatial distribution of clustering high-value or low-value spatial units [19]. The Getis–Ord G_i^* value based on the normal distribution hypothesis test is more sensitive than the LISA (Local Indicators of Spatial Association) method based on the random distribution hypothesis test [20].

In addition to using Getis–Ord G_i^*, spatial-temporal analysis can use kernel density analysis. Kernel density in the geographic information system is a method to determine whether or not an occurring phenomenon forms a cluster [21]. Kernel density analysis characterizes the horizontal pattern using spectral value information [22]. Kernel density is used to describe temporal and spatial heterogeneity [23]. The kernel method has been used in region analysis only since the 1990s. In the context of area analysis, this method describes the probability of observed objects in an area. This method begins by centering a bivariate of a density probability function with a unit volume (kernel) over each sample point [24]. A regular grid is then superimposed on the data, and a probability density estimate is calculated at each grid intersection by summing the volume of overlapping kernels. The density estimation at each grid intersection is used for the calculation of the bivariate kernel density estimation. The resulting kernel density estimation will have a relatively large value in areas with many sample points and low values in areas with few sample points. Predicted region estimates are obtained by drawing contour lines (isopleths) based on the number of kernel volumes at grid intersections. This isopleth defines predictive polygons at different probability levels whose area can be calculated.

Many autocorrelation analyses, such as Getis–Ord G_i^* and kernel density analysis, have been carried out to rehabilitate forest areas. Results of autocorrelation analysis in these studies are clusters of forest damage so that adaptive forest rehabilitation actions can be planned [25]. Studies on the spatial pattern of soil erosion risk on agricultural land show the impact of soil erosion, including problems of agricultural soil fertility [26]. Ord G_i^* and kernel density analysis can also analyze clusters and densities of earthquake events to examine clusters with various magnitudes [27]. Kernel density analysis has also been used to estimate the temporal and spatial patterns of carbon emissions; the results are used to plan efforts to achieve carbon emission reduction [23].

Forest and land fires are included in the geographical data, so they can be analyzed using Getis–Ord G_i^* analysis and kernel density analysis. The analysis helps reveal the spatial pattern of forest and land fires so that strategies for fire management, mitigation, and prevention can be designed [28, 29]. Unfortunately, studies on spatial patterns of land and forest fires and fire density at various national and regional scales are still rarely carried out [30], including in Indonesia. Kernel density analysis has been proven to be accurate for analyzing the spatiotemporal pattern of land fires [31, 32], so it is appropriate to use it in analyzing forest and land fires in fire-prone areas in Indonesia, such as South Kalimantan dominated by wetlands and peatlands.

The pattern and density of forest and land fires are useful for determining priority areas in handling forest and land fires in South Kalimantan since forest and lands fires have increased every year in the region. Based on data from http://sipongi.menlhk.go.id, fires covered 2,331.96 hectares of land in 2016, 8,290.34 hectares in 2017, and 9,8637.99 hectares in 2018 and increased to 137,848.00 hectares in 2019. The increasing land fires were due to the long dry season and the suboptimal handling [33]. Programs to manage burned forests and land areas, especially peatlands, have been widely carried out, such as by the Peat and Mangrove Restoration Agency (*Badan Restorasi Gambut dan Mangrove* (BRGM)) from 2016 to the present time, including in South Kalimantan [31, 32]. However, such programs were suboptimal because they could only restore limited areas while fires happened in such vast areas. This study focuses on areas with the densest fires based on the results of the spatiotemporal analysis and fire density analysis, so responsible government agencies like BRGM can set up a priority in handling fires. This study aims to analyze the spatiotemporal pattern of fires and fire density in fire-prone areas in Indonesia.

2. Materials and Methods

2.1. Research Location. The study took place in South Kalimantan Province with coordinates 5° 20′-1° 10′ S, 114° 0′-117° 40′ E with an area of 38,744 km^2. South Kalimantan experiences land fires every year and is a priority area for peat restoration [33, 34]. The research location is shown in Figure 1.

2.2. Data. The primary data for this research are the burned areas for four years from 2016 to 2019. The data come from the website http://sipongi.menlhk.go.id/, the official website of the Ministry of Forestry and Environment of the Republic of Indonesia. The fire data on the website come from NOAA (National Oceanic and Atmospheric Administration) data. The number of burned areas each year is shown in Table 1.

2.3. Analysis of Spatiotemporal Patterns with Hot Spot Analysis (Getis–Ord G_i^*). The analysis used to determine the pattern of land fires was the hot spot analysis. The hot spot analysis is used to calculate Getis–Ord G_i^* statistics on each dataset feature [35]. The calculation results will show the z-score and p value in each feature with a high or low value in the spatial cluster. This analysis considers each adjacent feature. Features with a high value are attractive but not necessarily statistically significant. A statistically significant hot spot has a high value and is surrounded by other features with a high value as well. The number of local features and their neighbors is compared proportionally to the sum of all features; when the local number is very different from the expected local number and the

Figure 1: Research location.

Table 1: Data on burned areas.

Number	Year	Number of burned areas (dots)
1	2016	43
2	2017	63
3	2018	191
4	2019	424

Source: http://sipongi.menlhk.go.id/.

difference is too large to be the result of a random chance, the z-score results are statistically significant [36]. The larger the positive z-score value, the more intense the grouping to form a hot spot, and vice versa—the smaller the negative z-score value, the more intense the grouping to form a cold spot [36, 37]. The formula of the Getis–Ord G_i^* is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{x}\sum_{j=1}^{n} w_{i,j}}{\sqrt[s]{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]/n-1}},$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}, \quad (1)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2},$$

where G_i^* = Ord G_i^* value; x_j = value or j feature attributes; w_{ij} = spatial weight between i and j features; $\overline{X}$ = average value; S = standard deviation; and n=number of features.

Hot spot analysis identifies significant hot spots and cold spots using the Getis–Ord G_i^* statistics using a set of weighting features. Weighting features are based on the field attribute selected from the analyzed layer. The neighborhood of each feature is compared with the study area to determine the value of each feature [37]. The value of z-score is interpreted in the hot spot analysis. The guideline for interpreting the z-score is presented in Table 2.

2.4. Analysis of Burned Area Density (Kernel Density). The probability density function is a fundamental concept in statistics. A random number X is considered with a probability density function f. The specific f function gives an overview of the distribution of X and allows the probability associated with X to be found in that relationship. Kernel density analysis calculates the density of features in the surrounding environment. One feature can be heavier than the other due to the meaning of the feature itself [39].

The algorithm used to determine the default search radius is also known as bandwidth. First, the mean center of

Table 2: Guideline in interpreting the z-score value in hot spot analysis.

No.	z-score	Interpretation
1	<−2.58	Cold spot- 99% confidence
2	−2.58 to −1.96	Cold spot- 95% confidence
3	−1.96 to −1.65	Cold spot- 90% confidence
4	−1.65 to 1.65	Not significant
5	1.65 to 1.96	Hot spot- 90% confidence
6	1.96 to 2.58	Hot spot- 95% confidence
7	>2.58	Hot spot- 99% confidence

Source: [38].

the input point is calculated if a population field other than none is selected, and the value of that field will weigh all the following calculations. Then, the distance from the mean center is calculated for all points. Next, the median of the distance (Dm) is calculated. Finally, the standard distance (SD) and the bandwidth with the radius search formula are calculated, as presented in the following [39]:

$$\text{Search radius} = 0.9 \times \min\left(\text{SD}, \sqrt{\frac{1}{\ln(2)}} \times \text{Dm}\right) \times n^{-0.2}, \tag{2}$$

where SD = standard distance, Dm = median distance, and n = number of points analyzed.

The steps taken to make a density analysis at the burned areas can be formulated as an analysis model shown in Figure 2.

3. Result and Discussion

3.1. The Spatiotemporal Pattern of Burned Areas in South Kalimantan. Burned areas in South Kalimantan Province continue to increase even though efforts have been made to reduce forest and land fires. There were 42 burned points in 2016, 63 in 2017, 191 in 2018, and 424 in 2019. The spatiotemporal pattern analysis helps identify fire patterns in an area and the risk of fire recurrence in the same area. Hot spot analysis can be used to analyze the spatial pattern of the burned area. Table 3 and Figure 3 describe the clusters of burned areas in South Kalimantan from 2016 to 2019. Moran's index value and z-value were obtained directly from the Getis–Ord G_i^* analysis (Table 3). Moran's index value and z-value are used to identify grouping or scattered data. The trend includes cold spots if the z-score is negative and hot spots if the z-score is positive.

In 2016, clusters of burned areas with hot spots (90%) were found in South Hulu Sungai Regency, Central Hulu Sungai Regency, and North Hulu Sungai Regency. Other regencies had cold spots with a confidence level of 99% (Figure 3). Table 3 shows that the z-score is dominated by negative values, which means a tendency to form cold spots. The two positive z-score values confirm a tendency to form hot spots with a value of 0.1019 to 0.1572 in three regencies. The negative Morgan index value indicates a random distribution of burned areas in 2016. Clusters of burned areas in South Kalimantan were formed in areas with low–medium vegetation density (Figure 4), which are peatlands. Shrubs and plantation areas dominate peatlands.

The cluster of burned areas in South Kalimantan in 2017 was found in Tabalong Regency with a 95% confidence level for hot spots. The cold spot cluster was found in Kotabaru Regency with a 95% confidence level (Figure 3). Other regencies belonged to the nonsignificant category. Table 3 shows that the z-score is dominated by negative values, which means a tendency to form cold spots. There are three positive z-score values, which means a tendency to form hot spots with an index value of around 0.0886 to 0.3884 in Tabalong Regency. The negative Morgan index value indicates the random distribution of burned area in 2017, as in 2016. Clusters of burned areas were found in areas with medium vegetation density, which are plantation areas (Figure 4).

In 2018, clusters of burned areas were found in Tanah Laut Regency, Banjar Regency, and Banjarbaru City, with a 90%-to-95% confidence level for hot spots (Figure 3). Other regions belonged to the nonsignificant category. Table 3 shows that the z-score is dominated by positive values, which means a tendency to form hot spots. The z-score value is positive, ranging from −1.65 to 1.65, with the highest value being 1.4177 and the lowest value being 1.0278. The positive Morgan index value in 2018 indicates that burned areas were clustered in the three regencies. Banjar and Banjarbaru have medium vegetation density and are peatlands, while Tanah Laut has medium vegetation density and is a plantation area (Figure 4).

In 2019, clusters of burned areas were found in Barito Kuala Regency, Banjar Regency, Tanah Bumbu Regency, Kotabaru Regency, and Banjarbaru City, with a confidence level of 90% to 99% for hot spots. Table 3 shows that the z-score is dominated by positive values, which means a tendency to form hot spots. The z-score value is positive, ranging from >2.5 and 1.96 to 2.58, with the highest value being 4.4966 and the lowest value being 1.6368. The positive Morgan index value in 2019 indicates that burned areas were clustered in the five regencies. Barito Kuala, Banjarbaru, and Banjar have medium vegetation density and are peatlands, while Tanah Bumbu and Kotabaru have medium vegetation density and are plantation areas (Figure 4).

The spatiotemporal pattern from 2016 to 2019 confirmed that burned areas in South Kalimantan were clustered in the western part of the province with different clusters each year. The burned area clusters have similarity in the land cover density—the low–medium density. The western region of South Kalimantan is a peatland area, and land conversion to plantation increases each year. Peatlands cover 331,629.00 hectares of South Kalimantan, distributed in the western part of the region [40]. Oil palm plantations are the type of plantation developed rapidly from scrubland in South Kalimantan. Changes in land cover from 1988 to 2014 were forest to secondary forest to scrub or old scrub to oil palm [41]. Data from the Ministry of Forestry and Environment in 2019 show that, out of 1,828,646 hectares of land in South Kalimantan, the largest agricultural area is dryland agriculture mixed with shrubs (391,256 hectares) and rice fields (325,730 hectares) [42].

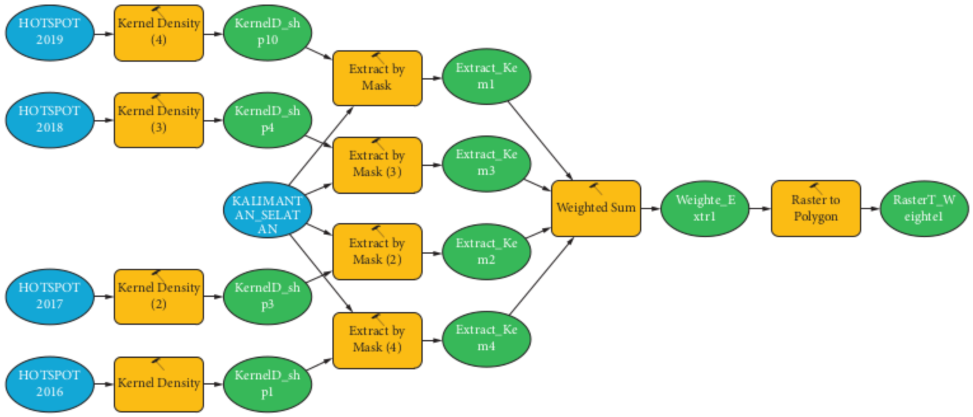

Figure 2: Analysis model of the burned area density.

Table 3: Data of global Moran's I summary of 2016–2019.

2016		2017		2018		2019	
Moran's index	z-score	Moran's index	z-score	Moran's index	z-score	Moran's index	z-score
−0.0093	0.1572	−0.0629	−0.8569	0.0394	1.3508	0.0447	1.6368
−0.0162	0.1019	−0.0654	−0.9152	0.0275	1.1115	0.0517	2.3253
−0.0393	−0.1236	−0.0495	−0.6322	0.0277	1.2250	0.0559	3.0498
−0.0318	−0.0536	−0.0442	−0.5269	0.0214	1.1031	0.0427	2.7914
−0.0331	−0.0705	−0.0362	−0.3633	0.0213	1.2236	0.0438	3.3053
−0.0496	−0.0270	−0.0275	−0.1604	0.0224	1.4065	0.0428	3.6308
−0.0551	−0.0270	−0.0447	−0.5968	0.0186	1.3422	0.0043	4.0809
−0.0788	−0.0270	−0.0174	0.0886	0.0111	1.0278	0.0399	4.1935
−0.0872	−0.0270	−0.0062	0.3848	0.0121	1.1631	0.0370	4.2883
−0.1056	−0.0270	−0.0066	0.3884	0.0149	1.4177	0.0351	4.4996

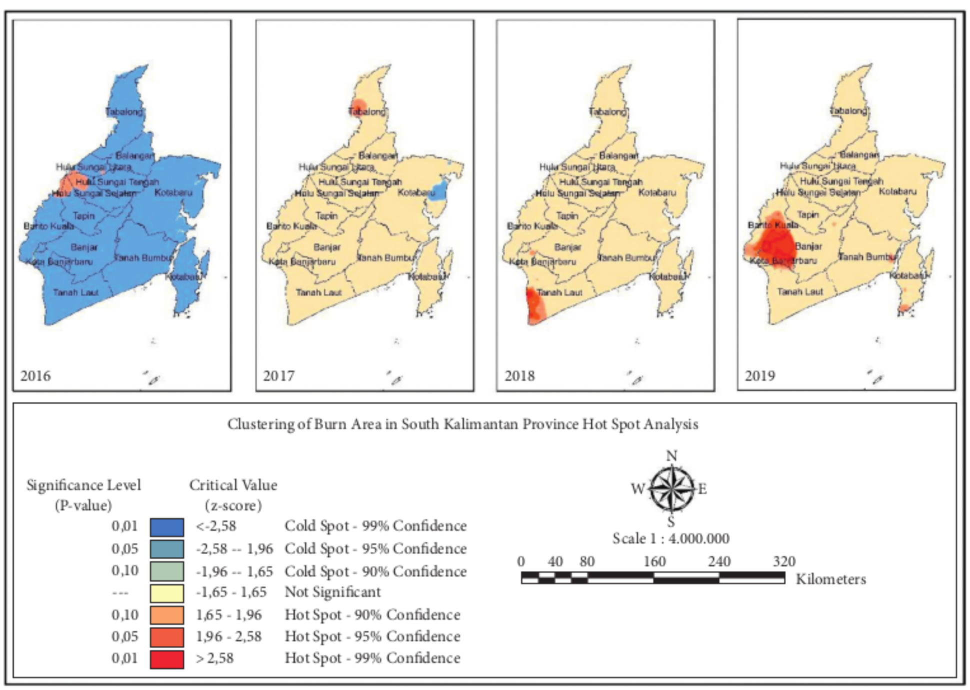

Figure 3: Clustering of burned areas in South Kalimantan.

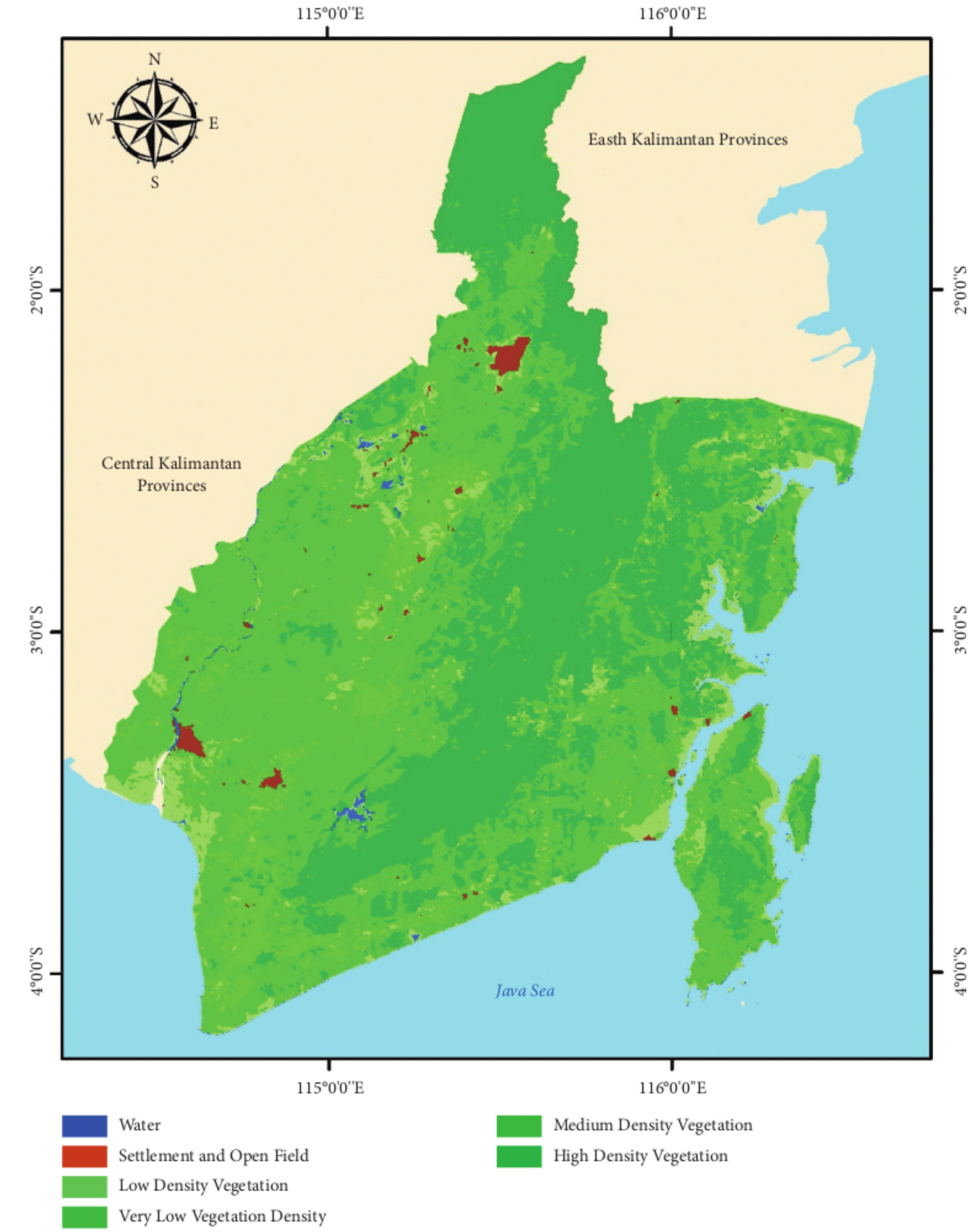

FIGURE 4: Land cover in South Kalimantan Province (source: MODIS Global Land Cover).

3.2. Burned Area Density in South Kalimantan. Burned area density has changed from 2016 to 2019. The blue color on the map represents a low hot spot density, while the red color represents a high hot spot density. The weighted overlay sum from 2016 to 2019 on the hotspot density map produced a four-year burned area density pattern. The resulting range is 0 to 0.0949859, where the larger value indicates denser and more burned areas, depicted by the red area (Figure 5). In 2016, 2017, and 2018, the highest burned area density was found in Hulu Sungai Selatan Regency, with a value of 0.00505548, 0.0113421, and 0.0415729, respectively. In 2019, the highest hot spot density of 0.0581646 was in Banjar Regency.

The fire density results showed the consistency of high fire density in Hulu Sungai Selatan Regency, with an index value ranging from 0.03 to 0.09. Another area with a high

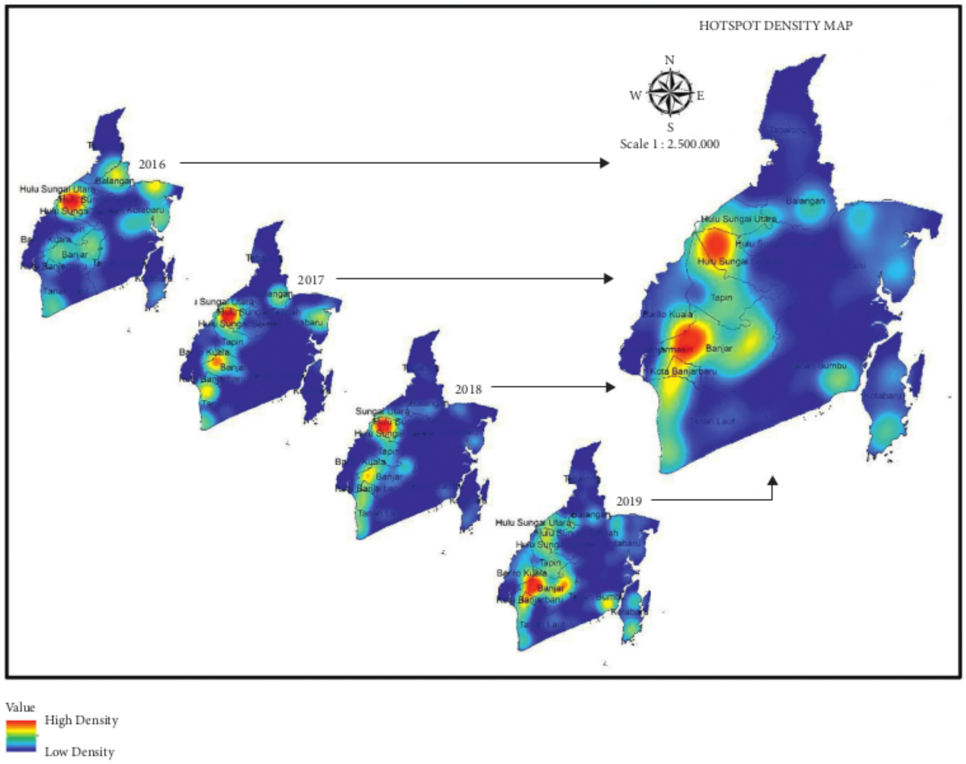

FIGURE 5: Map of land fire density in South Kalimantan Province.

variation in the average index value was the west side of Banjar Regency, with an index value ranging from 0.03 to 0.09. In contrast to the high average variation of burned areas in Hulu Sungai Selatan Regency, Banjar Regency showed a relatively low-to-medium variation from 2016 to 2018. The highest increase in index value occurred in 2019. Apart from these two areas, several other areas showed dynamics of burned area density. Balangan Regency and the west side of Tanah Laut Regency had quite varied dynamics over four years.

The pattern of land fire density using the kernel density method was similar to the pattern of the hot spot analysis; fires in South Kalimantan repeatedly occurred in the western region with high fire density from 2016 to 2019 (Figure 5). The western part of the region is peatlands and converted land with low–medium vegetation density (Figure 4). Land fires in the middle-eastern part of South Kalimantan occurred in low density marked in the blue color on the map (Figure 5). The middle-eastern part of South Kalimantan has a high vegetation density (Figure 4); it is the Meratus conservation area, so there is no fire.

This spatial pattern shows that peatlands must be a priority for continuous monitoring and handling of forest and land fires. The western part of South Kalimantan, including Barito Kuala Regency, South Hulu Sungai Regency, Tapin Regency, Tabalong Regency, and North Hulu Sungai Regency, has been a part of the peatland restoration area from 2016 to these days. The peat restoration covers 38,762 hectares of land [43]. This number, however, is far below the number of the burned area, which covered 137,848 hectares of land according to data from http://sipongi.menlhk.go.id in 2019. Some areas with high fire density, such as in Banjar and Banjarbaru, are also not included in the restoration area, so the handling of land fires in South Kalimantan has not been optimal.

Burned area patterns and burn area density can be analyzed using the Geographic Information System (GIS). The GIS can determine clusters of burned areas and fire density, as shown in Figures 3 and 5. GIS analysis is advantageous in classifying burned areas spatially. Spatial analysis can determine fire density and repeatedly burned areas [44]. The spatial analysis helps determine priority areas in handling forest and land fires [45].

The pattern of land fires and the high variation in the average value of the burned area density index also indicate the high intensity of fires in the area. The area with a clustered pattern with a high index value, like the western area of South Kalimantan, indicates a high fire intensity. The eastern side of South Kalimantan is a cold spot and has a low density of land fires. Land cover changes may be one cause of such a situation. The eastern side of South Kalimantan is the largest area with a low burned area density index value. This area is dominated by dense vegetation cover, which is a forest area and a conservation area of the Meratus Mountains. Forest areas have high fire resistance, so they are not easily burned [10, 46].

Overall, the land cover of South Kalimantan is mainly made up of vegetation with low–medium vegetation density. Peatlands are the dominant morphological condition on the west side of South Kalimantan. Burning is a method that is widely used in the conversion of peatlands for plantations. Land conversion has been proven to cause even severe land fires [47]. The dry season is when intense fires occur because dry peatlands are easier to burn. The length and difficulty of fighting fires on peatlands make land fires often detected in this area [33].

The utilization of data from the findings of this study is very important for forest and land fire disaster management in South Kalimantan, especially for the local government. The results of this study add to the information regarding the study of spatial patterns of forest and land fires as well as the density of fires at regional scales which are still rarely carried out. The finding can be used to determine priority locations for handling forest and land fires. The restoration program will be more targeted, in areas where fires occur repeatedly every year.

Overall, the Getis–Ord G_i^* analysis (hot spot analysis) and kernel density analysis can analyze the spatial pattern of land fires in South Kalimantan. Several studies using Getis–Ord G_i^* analysis and kernel density analysis confirm that both methods effectively measure the level of spatiotemporal clustering patterns [48]. However, the map generated by the kernel density analysis must be analyzed together with the hot spot analysis to be statistically significant [49]. Other studies show that the kernel density analysis is quite accurate for analyzing spatiotemporal patterns even though it is considered a nonstatistical approach [44].

4. Conclusions

The spatiotemporal pattern of burned areas occurs in several areas in South Kalimantan characterized by hot spots with a confidence level of 90% to 99%. Clusters of burned areas occur in areas with medium vegetation density, which are peatlands and plantation areas. The high fire density also occurs in several areas, such as Hulu Sungai Selatan Regency and Banjar Regency. The high fire density occurs in areas with medium vegetation density and peatlands. The spatiotemporal pattern and fire density can help determine the priority in handling land fires. In South Kalimantan, the priority is regencies with hot spot burned areas and high fire density, especially in areas with medium vegetation density or scrubland on peatlands and plantation areas. The two analyses have revealed the spatial pattern of forest and land fires in South Kalimantan. This study recommends using other autocorrelation methods to better understand the spatiotemporal patterns of forest and land fires and compare the accuracy of these various methods for best policy making related to forest and land fire risks.

Data Availability

The data supporting this article are from datasets which have been cited.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] B. Kumari and A. Pandey, "MODIS based forest fire hotspot analysis and its relationship with climatic variables," *Spatial Information Research*, vol. 28, 2019.

[2] H. Purnomo, B. Shantiko, S. Sitorus et al., "Fire economy and actor network of forest and land fires in Indonesia," *Forest Policy and Economics*, vol. 78, pp. 21–31, 2017.

[3] Z. D. Tan, L. R. Carrasco, and D. Taylor, "Spatial correlates of forest and land fires in Indonesia," *International Journal of Wildland Fire*, vol. 29, no. 12, pp. 1088–1099, 2020.

[4] T. Turmudi, P. Kardono, P. Hartanto, and Y. Lumban Gaol, "Forest and land fire prevention through the hotspot movement pattern approach," *IOP Conference Series: Earth and Environmental Science*, vol. 123, p. 12027, 2018.

[5] D. Arisanty, M. Z. A. Anis, H. P. N. Putro, K. P. Hastuti, and P. Angriani, "Social vulnerability of land fires in Banjarbaru," in *Proceedings of the 2020 2nd International Conference on Social Sciences Education (ICSSE 2020)*, pp. 262–265, Atlantis Press, Dubai, UAE, March 2021.

[6] E. Wardihani, M. Ramdhani, A. Suharjono, and F. Saifullah, "Real-time forest fire monitoring system using unmanned aerial vehicle," *Journal of Engineering Science and Technology*, vol. 13, pp. 1587–1594, 2018.

[7] F. Ahmad, L. Goparaju, and A. Qayum, "Himalayan forest fire characterization in relation to topography, socio-economy and meteorology parameters in Arunachal Pradesh, India," *Spatial Information Research*, vol. 26, no. 3, pp. 305–315, 2018.

[8] A. Laha, S. Singh, U. Mishra, and M. Singh, "Estimating spatiotemporal dynamics of forest fire hazard using analytical hierarchy process and geostatistical methods in similipal biosphere reserve, India," 2021.

[9] F. Ahmad and L. Goparaju, "Forest fire trend and influence of climate variability in India: a geospatial analysis at national and local scale," *Ekológia*, vol. 38, no. 1, pp. 49–68, 2019.

[10] O. Abdi, B. Kamkar, Z. Shirvani, J. A. Teixeira da Silva, and M. F. Buchroithner, "Spatial-statistical analysis of factors determining forest fires: a case study from Golestan, Northeast Iran," *Geomatics, Natural Hazards and Risk*, vol. 9, no. 1, pp. 267–280, 2018.

[11] C. Bitter, G. F. Mulligan, and S. Dall'erba, "Incorporating spatial variation in housing attribute prices: a comparison of geographically weighted regression and the spatial expansion method," *Journal of Geographical Systems*, vol. 9, no. 1, pp. 7–27, 2007.

[12] K. Ganguly, R. Kumar, K. Reddy, P. J. Rao, M. Saxena, and G. R. Shankar, "Optimization of spatial statistical approaches to identify land use/land cover change hot spots of Pune region of Maharashtra using remote sensing and GIS techniques," *Geocarto International*, vol. 32, 2016.

[13] D. Ivajnsic, M. Kaligarič, and I. Žiberna, "Geographically weighted regression of the urban heat island of a small city," *Applied Geography*, vol. 53, pp. 341–353, 2014.
[14] F. Zhao, L. Tang, Q. Qiu, and G. Wu, "The compactness of spatial structure in Chinese cities: measurement, clustering patterns and influencing factors," *Ecosystem Health and Sustainability*, vol. 6, no. 1, Article ID 1743763, 2020.
[15] J. Gong, J. Lee, S. Zhou, and S. Li, "Toward measuring the level of spatiotemporal clustering of multi-categorical geographic events," *ISPRS International Journal of Geo-Information*, vol. 9, no. 7, p. 440, 2020.
[16] R. Rozpondek, K. Wancisiewicz, and M. Kacprzak, "GIS in the studies of soil and water environment," *Journal of Ecological Engineering*, vol. 17, no. 3, pp. 134–142, 2016.
[17] J. M. Sánchez Martín, J. Rengifo Gallego, and R. Morato, "Hot spot analysis versus cluster and outlier analysis: an enquiry into the grouping of rural accommodation in Extremadura (Spain)," *International Journal of Geo-Information*, vol. 8, p. 176, 2019.
[18] D. K. Wright, J. Kim, J. Park, J. Yang, and J. Kim, "Spatial modeling of archaeological site locations based on summed probability distributions and hot-spot analyses: a case study from the three kingdoms period, Korea," *Journal of Archaeological Science*, vol. 113, Article ID 105036, 2020.
[19] Y. Hao, Y. Xu, J. Zhang et al., "Relationship between forest resources and economic growth: empirical evidence from China," *Journal of Cleaner Production*, vol. 214, pp. 848–859, 2019.
[20] A. Getis and J. Aldstadt, "Constructing the spatial weights matrix using a local statistic," *Geographical Analysis*, vol. 36, no. 2, pp. 90–104, 2004.
[21] B. Lee, "Differences in network-based kernel density estimation according to pedestrian network and road centerline network," 한국측량학회지, vol. 36, no. 5, pp. 335–341, 2018.
[22] S. Shirowzhan, S. Lim, J. Trinder, H. Li, and S. M. E. Sepasgozar, "Data mining for recognition of spatial distribution patterns of building heights using airborne lidar data," *Advanced Engineering Informatics*, vol. 43, Article ID 101033, 2020.
[23] W. Li, W. Sun, G. Li, P. Cui, W. Wu, and B. Jin, "Temporal and spatial heterogeneity of carbon intensity in China's construction industry," *Resources, Conservation & Recycling*, vol. 126, 2017.
[24] B. W. Silverman, *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, London, UK, 1986.
[25] F. Rossi and G. Becker, "Creating forest management units with Hot Spot Analysis (Getis-Ord G_i^*) over a forest affected by mixed-severity fires," *Australian Forestry*, vol. 82, no. 4, pp. 166–175, 2019.
[26] D. I. T. Al-Azzawi, "Spatial analysis of agricultural land erosion using the statistical model of Getis-Ord G_i^* in Saladin Governorate," *Journal of Al-Frahedis Arts*, vol. 10, no. 34, 2018.
[27] B. Aslam and F. Naseer, "A statistical analysis of the spatial existence of earthquakes in Balochistan: clusters of seismicity," *Environmental Earth Sciences*, vol. 79, 2020.
[28] A. Firoz, L. Goparaju, A. Qayum, and S. M. S. Quli, "Forest fire trend analysis and effect of environmental parameters: a study in Jharkhand state of India using geospatial technology," *World Scientific News*, vol. 90, pp. 31–50, 2017.
[29] M. Shekede, I. Gwitira, and C. Mamvura, "Spatial modelling of wildfire hotspots and their key drivers across districts of Zimbabwe, Southern Africa," *Geocarto International*, vol. 36, pp. 1–16, 2019.
[30] N. Monjarás-Vega, C. Briones-Herrera, D. Vega-Nieva, and W. Jolly, "Predicting forest fire kernel density at multiple scales with geographically weighted regression in Mexico," *The Science of the Total Environment*, vol. 718, Article ID 137313, 2020.
[31] A. S. Alisjahbana and J. M. Busch, "Forestry, forest fires, and climate change in Indonesia," *Bulletin of Indonesian Economic Studies*, vol. 53, no. 2, pp. 111–136, 2017.
[32] A. Wijaya, H. Chrysolite, M. Ge, and K. Austin, *How Can Indonesia Achieve its Climate Change Mitigation Goal? An Analysis of Potential Emissions Reductions from Energy and Land-Use Policies*, World Resources Institute, Washington D.C., USA, 2017.
[33] D. Arisanty, K. Jędrasiak, I. Rajiani, and J. Grabara, "The destructive impact of burned peatlands to physical and chemical properties of soil," *Acta Montanistica Slovaca*, vol. 25, no. 2, pp. 213–223, 2020.
[34] D. Arisanty, S. Adyatma, M. Muhaimin, and A. Nursaputra, "Landsat 8 OLI TIRS imagery ability for monitoring post forest fire changes," *Pertanika Journal of Science & Technology*, vol. 27, no. 3, pp. 1105–1120, 2019.
[35] A. Getis and K. Ord, "The analysis of spatial association by use of distance statistics," *Geographical Analysis*, vol. 24, pp. 189–206, 1992.
[36] J. K. Ord and A. Getis, "Local spatial autocorrelation statistics: distributional issues and an application," *Geographical Analysis*, vol. 27, no. 4, pp. 286–306, 2010.
[37] E. Pimpler, *Spatial Analytics with ArcGIS*, Packt Publishing, Birmingham, England, 2017.
[38] Z. Cheng, Z. Zu, and J. Lu, "Traffic crash evolution characteristic analysis and spatiotemporal hotspot identification of urban road intersections," *Sustainability*, vol. 11, no. 1, p. 160, 2018.
[39] ESRI, *How Kernel Density Works—ArcGIS Pro | Documentation*, ESRI, Redlands,, CA, USA, 2014, https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm.
[40] Wahyunto, "Maps of peatland distribution area and carbon content in Sumatra," in *Wetlands International-Indonesia Programme*Bogor, Jawa Barat, Indonesia, 2003.
[41] A. L. Rizqi, "Identification of changes in wetland cover in the Negara River Delta and Barito River Deltas, South Kalimantan Province," Thesis. IPB University, Bogor, Indonesia, https://repository.ipb.ac.id/handle/123456789/105604, 2021.
[42] Antara News, "KLHK presents data on land cover changes in the Barito watershed, South Kalimantan," 2021, https://www.antaranews.com/berita/1979304/klhk-paparkan-data-perubahan-tutupan-lahan-das-barito-kalsel.
[43] BRG, "Strategic plan peatland restoration agency 2016-2020," 2017, https://brg.go.id/rencana-strategis-badan-restorasi-gambut-2016-2020/.
[44] S. Reddy, N. Bird, S. Sreelakshmi, and P. Diwakar, "Identification and characterization of spatio-temporal hotspots of forest fires in South Asia," *Environmental Monitoring and Assessment*, vol. 191, 2020.
[45] E.-S. Zahran, S. Shams, and S. Mohd Said, "Validation of forest fire hotspot analysis in gis using forest fire contributory factors," *Systematic Reviews in Pharmacy*, vol. 11, pp. 249–255, 2020.
[46] A. Tariq, H. Shu, S. Siddiqui et al., "Forest fire monitoring using spatial-statistical and geo-spatial analysis of factors determining forest fire in Margalla Hills, Islamabad, Pakistan," *Geomatics, Natural Hazards and Risk*, vol. 12, no. 1, pp. 1212–1233, 2021.

[47] R. Walker, J. Coop, S. Parks, and L. Trader, "Fire regimes approaching historic norms reduce wildfire-facilitated conversion from forest to non-forest," *Ecosphere*, vol. 9, 2018.
[48] M. Souris and F. Demoraes, "Improvement of spatial autocorrelation, kernel estimation, and modeling methods by spatial standardization on distance," *ISPRS International Journal of Geo-Information*, vol. 8, no. 4, p. 199, 2019.
[49] M. Kalinic and J. Krisp, "Kernel Density Estimation (KDE) vs. hot-spot analysis-detecting criminal hot spots in the city of San Francisco," 2018.

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