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CLUSTER MAPPING OF HOTSPOTS USING KERNEL DENSITY ESTIMATION IN WEST KALIMANTAN

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ABSTRACT

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Forest and land fires pose a recurring concern every year in Indonesia, often taking place in West Kalimantan Province, particularly during the dry season. This study aims to use the Kernel Density Estimation (KDE) to categorize the data of the hotspots in the province of West Kalimantan according to their density and to map the cluster level of the fire risks in the region. The data utilized in this study are secondary data obtained from the images of the MODIS (Moderate Resolution Imaging Spectroradiometer) instrument, which are available on firms.modaps.eosdis.nasa.gov and provided by NASA. The data focuses on hotspots dispersed across West Kalimantan province during 2020. The variables examined in the study were the confidence level (≥ 80%) of forest and land fire hotspots, the distance from each point to the nearest river, and the distance from each point to the nearest road. The kernel density estimation method with a Gaussian kernel function yielded clustering results into three distinct groups according to their vulnerability levels. Low vulnerability areas comprise Cluster 1, which consists of 127 points or 50.97% of the total hotspots. Medium vulnerability areas belong to Cluster 2, which has 47 points or 30.32% of the total. Cluster 3 includes high vulnerability locations, consisting of 29 points or 18.71% of the total. The most susceptible areas to forest and land fires are located within the Ketapang regency.

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1. INTRODUCTION

Wildfires on land and in forests occurred frequently in the province of West Kalimantan, especially during the dry season. West Kalimantan Province is located between lines 108°0'E and 114°10'E and 2°08'N and 3°05'S. Geographically, the Equator (latitude 0°) passes through the Province of West Kalimantan, giving it a tropical climate with warm temperatures. The Ministry of Environment and Forestry (KLHK) reports that there are 1.6 million hectares of peatland and 8.2 million hectares of forest area in West Kalimantan. The extent of peatland makes West Kalimantan one of the most vulnerable provinces and a priority in mitigating wildfires on land and in forests [1]. Forest and land fires can be caused by various factors such as environmental or biophysical factors and human activity or anthropogenic factors [2]. Factors related to human activity, such as the level of accessibility and the proximity to human activity centers, constitute the main causes of forest and land fire incidents [3].

Incidents involving land and forest fires entail various adverse consequences. In addition to causing environmental (biophysical) problems such as climate change, the emissions produced by wildfires also impact human health, including reduced visibility and lung disease. Forests, which are natural resources that drive local economies, lose their economic function as a result of the loss of forest ecosystems and other potentials they contain, such as biodiversity. The land area decreases, and hundreds of hectares of forest are damaged every year, which harms local and national economies [4].

A hotspot refers to a pixel that has a temperature value surpassing a certain threshold monitored by remote sensing satellites and can act as an indicator of forest and land fire events. A confidence level expressed as a percentage indicates the level of confidence that a monitored hotspot is a true fire occurrence. Regarding hotspot data, a confidence level of ≥ 80% signifies a high degree of assurance that the hotspots observed through imagery obtained from satellite data are genuine and actual wildfires [5]. Using hotspot data from the Geographic Information System (GIS) to identify areas with fire potential is one way to prevent forest fires. GIS provides tools that can assist in the identification and prioritization of geographical locations associated with events and hotspots. GIS enables the development of maps and the visualization of scenario outcomes [6]. Spatial information, which is the type of information processed by a GIS, refers to information that has a geographic orientation and is associated with a specific coordinate system as a reference frame [7].

Identifying the cluster in the area is one of the strategies to mitigate the forest and land fires. Kernel Density Estimation (KDE) is one of the clustering methods that can be used to analyze hotspot data, and as a result, it can be used to anticipate potential forest and land fires. There is a substantial connection between density-based clustering and density estimation. The goal of density estimation is to determine the unknown probability density function by identifying dense regions of points, which can then be used for clustering. Kernel density estimation is a nonparametric technique that does not use a fixed probability model for the clusters. Instead, it attempts to directly estimate the underlying probability density at each point in the dataset [8]. Setiawan et al. found that KDE can represent data structures that are difficult to model by other functions very well [9]. Nanda et al. in 2019 applied the KDE method for mapping crime-prone areas in Semarang City and used this method as a clustering method to produce 5 clusters [10].

This research intends to categorize hotspot data in West Kalimantan based on density using KDE and mapping the cluster results. The use of KDE was chosen for this study because it is a statistical method that can estimate the probability distribution of a dataset, in this case, the hotspot data. KDE allows for the identification of areas with high hotspot density based on the calculation of kernel density. Furthermore, the Gaussian kernel function is a common choice for KDE due to its ability to capture the underlying structure of the data and provide a smooth estimate of the density function [11]. This study utilizes data on the points of forest and land fires in the province of West Kalimantan in 2020, which are derived from the image of the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument published by NASA through the website firms.modaps.eosdis.nasa.gov. From the data obtained, the variable confidence level, the distance of the point to the river, and the distance of the point to the road are analyzed using the algorithm. Furthermore, this study is anticipated to be utilized as a mode of disaster reduction to lessen the effect of losses owing to forest and land fires in the province of West Kalimantan.

2. RESEARCH METHODS

The study utilizes Kernel Density Estimation (KDE) to categorize hotspot data in West Kalimantan based on density. First, the data points for the hotspot locations in West Kalimantan are collected and ensured to be in a suitable format for processing. Second, a kernel function, such as the Gaussian kernel, is chosen and the bandwidth parameter is set. The kernel density estimate for each data point is then calculated by placing a kernel at each point and summing the kernels to generate a probability surface. Next, the densest points in the data set are identified, which are considered the core of each cluster. Each data point is assigned to the cluster with the highest density if it is not dense enough to be considered part of its cluster. Following the clustering process, the KDE is used to create a probability surface representing the data points' density. The clusters are visualized by mapping the density values to a color scale. Finally, the effectiveness of the clustering algorithm is evaluated by analyzing the resulting clusters and their characteristics [10], [12].

The following are the stages of data analysis using the kernel density estimation clustering method presented through a flow chart in Figure 1.

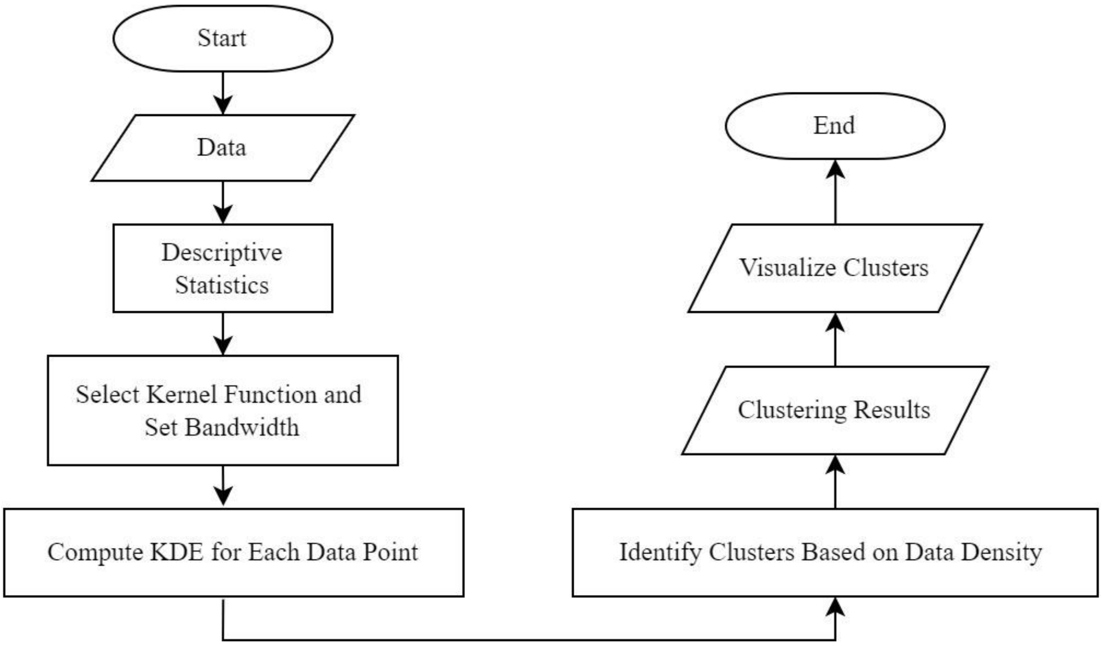


Figure 1. Research Flowchart

2.1 Data Sources

The data utilized in this study are secondary, namely data on forest and land fire hotspots in West Kalimantan in 2020 which were detected to have a confidence level $\geq 80\%$. The hotspot data was released by the National Aeronautics and Space Administration (NASA) through the website https://firms.modaps.eosdis.nasa.gov which was obtained from Terra and Aqua satellite images through the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument. The location of forest and land fire hotspot data in this study is spread across 10 regencies in West Kalimantan province. The data location hotspots can be visualized in **Figure 2.**

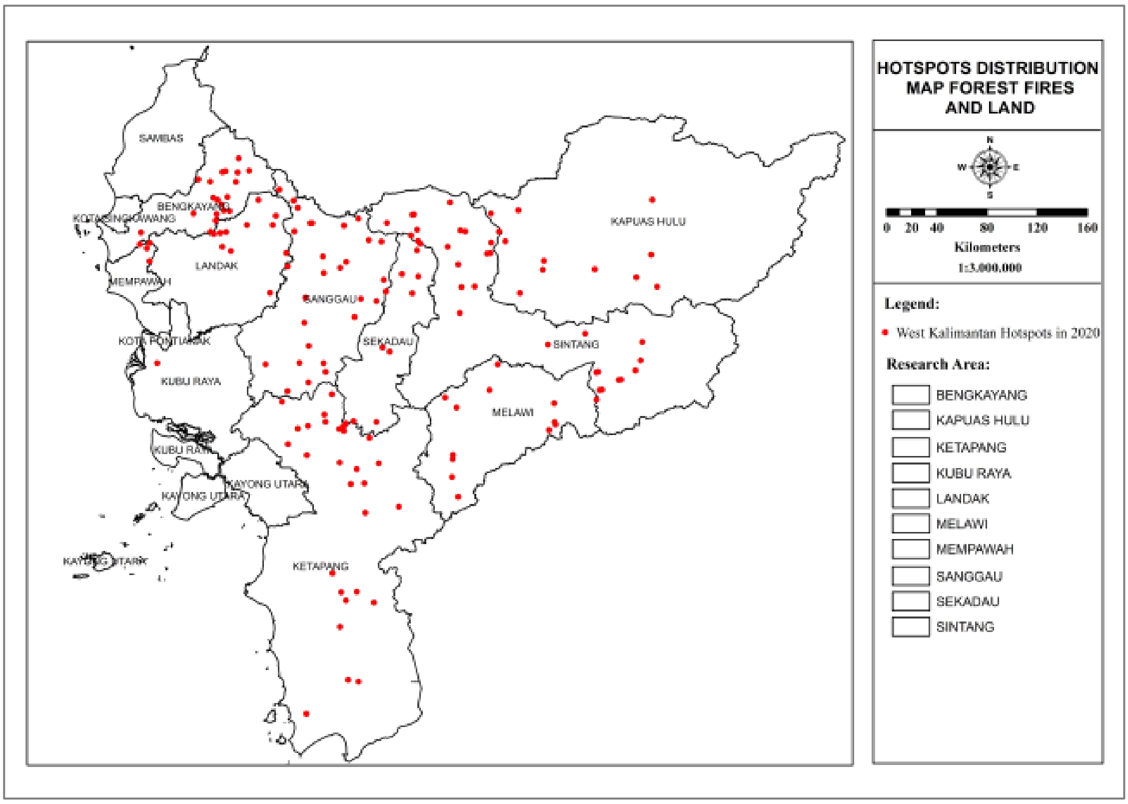


Figure 2. Distribution Map of Hotspots

Based on the data presented in **Figure 3**, the graph shows a notable increase in the number of hotspots or forest fires during August, September, and October.

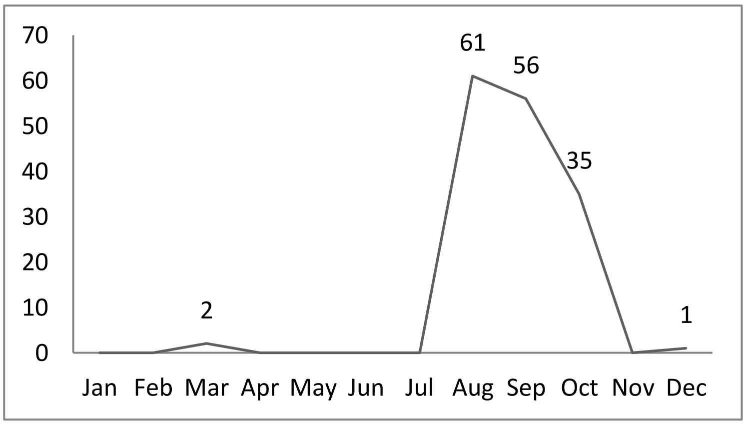


Figure 3. Plot of the Number of Hotspots from January–December 2020

The number of hotspot data spread across all West Kalimantan regencies for January - December 2020 with a confidence level of ≥ 80% amounted to 155 data, which are presented in **Table 1**.

Table 1. Data of Hotspots in West Kalimantan

No	Regency	Amount of Hotspots
1	Bengkayang	19
2	Kapuas Hulu	11
3	Ketapang	28
4	Kubu Raya	1
5	Landak	12
6	Melawi	13
7	Mempawah	3

No	Regency	Amount of Hotspots
8	Sanggau	29
9	Sekadau	10
10	Sintang	29
	Total	155

Table 1 shows that in West Kalimantan, hotspots with a confidence level of ≥ 80% are only found in 10 regencies. Singkawang City, Pontianak City, Sambas, and Kayong Utara Regency are areas that do not have hotspots with a confidence level of ≥ 80%. Sanggau Regency and Sintang Regency have the highest number of hotspots with 29 hotspots, while Kubu Raya Regency has the least number of hotspots, with 1 hotspot.

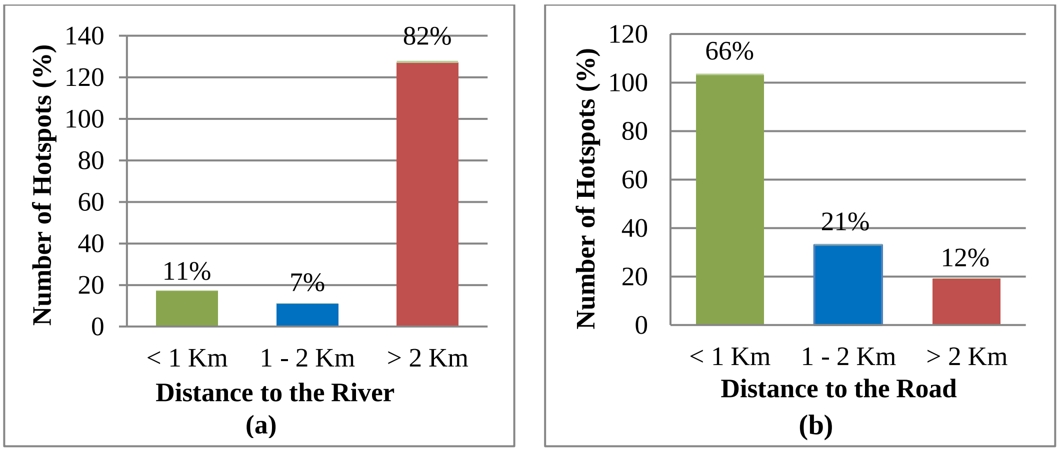


Figure 4. Bar Chart (a) Distance to the River and (b) Distance to the Road

Based on **Figure 4 (a)**, it can be seen that the fire hotspots are dominated by a considerable distance from the river or in areas with high vulnerability potential, amounting to 82% or 127 hotspots. In the variable distance to the river, the farther the distance of the hotspot to the river, the higher the risk of forest fires, on the other hand, the closer the distance of the hotspot to the river, the lower the potential for forest and land fires **[13]**.

The visualization of the distance from the hotspot to the road is presented in **Figure 4 (b)**. According to **Figure 4 (b)**, it is known that the fire hotspots are dominated by a fairly close distance from the road. The existence of roads that are easily accessible by humans can increase the risk of forest and land fires. This access makes it easier for people to interact and has a negative impact that triggers community negligence so that can cause fires that trigger forest and land fires. The closer the distance between hotspots and roads, the higher the risk of land and forest fires, and the farther away the road access, the lower the potential for forest and land fires **[14]**. In the category of distance to the road, fire hotspots are dominated in areas with high vulnerability potential, which amounts to 66% or 103 hotspots.

2.2 Probability Density Function

A probability density function is a mathematical function employed to depict the probability distribution of a continuous random variable. KDE employs this probability density function to approximate the shape of the data's density function. In KDE, each data point is smoothed into a spatial region surrounding it using a kernel function. Each data point's contribution is then summed to give an overall picture of the data structure and its density function. Suppose X is a continuous random variable defined in the set of real numbers. A function is called the density function of X, if its values $f(x)$ satisfy the following properties **[11]**:

- $f(x) \geq 0$, for all $x \in R$
- $\int_{-\infty}^{\infty} f(x)dx = 1$

2.3 Kernel Density Estimation (KDE)

Kernel density estimation is a nonparametric technique of estimating density functions that is commonly used in computational techniques that have a free distribution. In addition to the structure of data distribution that is not an issue, this method also does not use certain parameters as a benchmark for calculation [15]. KDE is a development of the histogram estimation method. Its primary objective is to estimate the probability density function of a data point in a plane with a specified radius [10]. KDE is a technique that can be used in detecting fire-prone areas because it is supported by the visualization of results that are easy to understand. KDE is evaluated by positioning a uniform curve on each data point and measuring the distance from the data point to a reference point by using a mathematical function (kernel function).

Kernel density estimation utilizes a kernel function (K) to determine the weight given to each data point based on its distance from the point that is to be estimated and a bandwidth (h) to determine the width of the interval. The choice of kernel function and bandwidth can affect the quality of the kernel estimator. Commonly used kernel functions include Gaussian, Epanechnikov, Quartic, Triangular, Uniform, and Biweight. The bandwidth determines the width of the interval and controls the trade-off between bias and variance in the estimation. A bandwidth value that is too small will produce estimates with high variance and low bias, while a bandwidth value that is too large will produce estimates with low variance and high bias [9].

In general, the kernel function (K) with bandwidth (h) is defined as follows.

$$K_h(x) = \frac{1}{h} K\left(\frac{x}{h}\right), for - \infty < x < \infty, h > 0 \tag{1}$$

Kernel estimate $\hat{f}(x)$ of original $f(x)$ assigns each i_{th} sample data point x_i a function $K(x)$ called a kernel function in the following way:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K(x) \left(\frac{X - x_i}{h}\right) \tag{2}$$

where x_i: $i = 1,2, \dots, n$, n : number of data, h: bandwidth value.

In this study, the Gaussian kernel function formulated in Equation (3) is used to estimate the density function of kernel density estimation [12].

$$\hat{f}(x) = \frac{1}{n} \sum_{i=1}^{n} \prod_{j=1}^{d} \frac{1}{h_j \sqrt{2\pi}} \exp^{-\frac{1}{2}\left(\frac{x_j - x_{i,j}}{h_j}\right)^2} \tag{3}$$

where,

$\hat{f}(x)$: estimated density function
n : the number of data points
x_i : the i-th data point, where $i = 1,2,3, \dots., n$
d : the number of features
x_j : the j-th feature of a data point, where $j = 1,2, \dots, d$
h_j : bandwidth value

2.4 Bandwidth Selection

In KDE, the smoothness of $\hat{f}(x)$ is determined by the kernel function and the smoothing parameter, also known as the bandwidth (h). The bandwidth controls the level of smoothness in the density estimate. If the bandwidth is too narrow, it will result in a density estimate that fluctuates and is rough, leading to a low variance relationship with the potential for significant bias. Conversely, if the bandwidth is too broad, it will result in a density estimate that is overly smooth and does not match the data pattern, also leading to low variance with a significant potential for bias [16]. In this study, the bandwidth selection method explores the use of fixed and adaptive bandwidths for density estimation with KDE in cluster analysis. Fixed bandwidth uses a constant value for all data points. When employing adaptive bandwidth, the bandwidth value is adjusted for each data point or a designated portion of the data distribution. To determine the smoothing parameter for density estimation using kernel estimation with either a fixed bandwidth or an adaptive bandwidth, the following equation can be used [17]:

$$h_j = \sigma_j \left(\frac{4}{(d+2)n}\right)^{\frac{1}{d+4}} \tag{4}$$

with,

$$\sigma_j = \sqrt{\frac{\sum(x_{ij} - \mu_j)^2}{n-1}} \tag{5}$$

where h_j: the bandwidth value at the j_{th} variable, σ_j: the standard deviation of data on the j_{th}variable, d: the number of variables, and n: The number of data.

3. RESULTS AND DISCUSSION

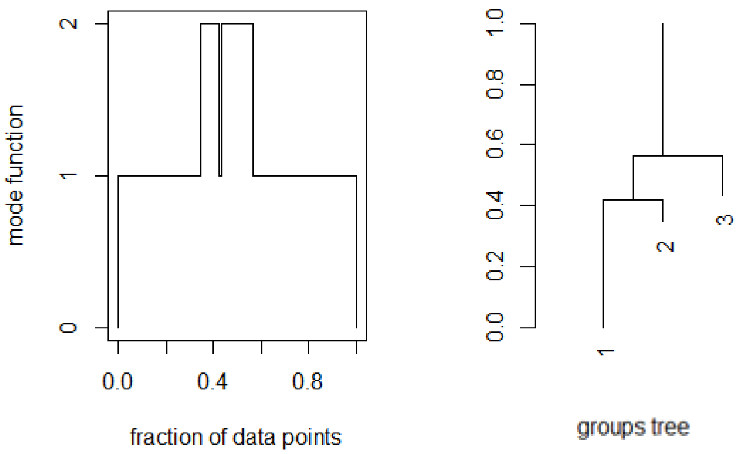
3.1 Clustering Using Kernel Density Estimation (KDE)

Kernel density estimation is a non-parametric statistical method used to estimate the probability density function of a distribution based on several observed data points. The bandwidth in this study was calculated using R-Studio software. The results of computing the optimal bandwidth value for each variable, consisting of confidence, distance from a hotspot to a river, and distance from a hotspot to a road are provided in Table 2.

Table 2. Bandwidth

Variable	Bandwidth Value
Confidence (%)	2.757
Distance to River (Km)	2.877
Distance to Road (Km)	0.611

The bandwidth used in this study is a fixed bandwidth, i.e., the same value is used in the density calculation for all data points. In this study, identifying clusters was done with the help of R-Studio software. This method does not have a special mechanism to automatically determine the number of clusters, therefore visualization is used to assist in cluster identification [12]. The results of cluster grouping are shown in Figure 5 as follows:



(a) **(b)**

Figure 5. Cluster Formation (a) Mode function, (b) Groups tree

In Figure 5 (a) the mode function identifies the number of clusters by looking at the number of prominent peaks. Each peak in the Mode Function indicates the mode of the density function, which represents a potential cluster in the data. The mode refers to the point in the data distribution that has the highest density. This point is considered to be the center of the cluster, as it represents the region of the highest density and data points adjacent to this point are considered to be part of the same cluster. **Figure 5 (b)** illustrates the hierarchical and clustering structure of the cluster, with the higher branches indicating larger clusters, and the lower branches indicating smaller ones. Three of these clusters exhibit higher densities than other regions in the data distribution.

The results of the research conducted show that the grouping of fire vulnerability levels in the province of West Kalimantan is divided into three clusters (groups). The KDE method allows for a deeper understanding of regional characteristics based on the density of data related to the potential for land and forest fires. To describe the characteristics of each cluster, the average value of each group was calculated. **Table 3** shows the average data for each cluster:

Table 3. Cluster Average Data

Cluster	Prone Level	Number of Hotspots	Average confidence (%)	Average Distance to River (Km)	Average Distance to Road (Km)
1	Low	79	84.02	3.602	1
2	Medium	47	86.53	13.082	0.793
3	High	29	96.62	6.013	0.132

According to the outcomes of the analysis using the KDE method, the characteristics of the three clusters formed can be identified. Cluster 1, which has a low level of vulnerability, consists of 79 hotspots spread across West Kalimantan Province. The KDE data density analysis results show that this cluster has an average confidence level of 84.02, indicating a high level of confidence in forest and land fires. However, the confidence level of cluster 1 is lower than that of clusters 2 and 3. Furthermore, cluster 1 has an average distance to rivers of 3,602 km, which is lower than that of cluster 2. This suggests that distance to rivers has less influence on forest and land fires. Moreover, the average distance to a road in cluster 1 is about 1 km, which indicates that the hotspots in this cluster are quite far from the road, where the average distance to a road in cluster 1 is higher than the other clusters, which identifies that forest and land fires are more vulnerable at a fairly close distance to the road, which also indicates that human activities can affect forest and land fires. The implications for local communities and policymakers in this cluster are that prevention and preparedness efforts can be tailored to the specific needs of this lower-risk zone, potentially focusing on public awareness campaigns and maintaining basic firefighting capabilities.

In cluster 2, which has a medium level of vulnerability, there are 47 hotspots spread across West Kalimantan Province. The results of the KDE analysis show that the average confidence level in this cluster is 86.53, indicating a higher level of confidence regarding the potential for forest and land fires. In cluster 2, it can also be seen that the average distance to the river is very far, which is around 13.082 Km. Then, it can be seen that the average distance to the road in cluster 2 is 0.793, which identifies a considerable distance from the road. In these areas, the fire risk is elevated, and a more proactive approach to fire mitigation may be warranted. Policymakers can consider enhancing early warning systems, strengthening coordination among various stakeholders, and increasing the availability of firefighting resources in these medium-risk areas.

Cluster 3 with a high level of vulnerability consists of 29 hotspots spread across West Kalimantan. In this cluster, it can be seen that the average confidence level is 96.62, which shows a very high level of confidence in the potential for forest and land fires. In addition, in cluster 3, the average distance to the river is 6.013 Km and the average distance to the road in cluster 3 is 0.132 Km which indicates that the potential for forest and land fires will be higher because the distance of the hotspots to the river is very far and the distance to the road is closer. The river functions as a natural barrier to the spread of fire, thereby reducing the vulnerability of areas in closer proximity to the river to the effects of fire in comparison to those situated at a greater distance from the river. Conversely, areas close to roads tend to exhibit elevated levels of human activity, including vehicular traffic, open burning, and other activities that can potentially ignite forest fires. The findings of this study have significant implications for both local communities and policymakers. Immediate action must be taken to enhance fire prevention and response capabilities in these high-risk areas. This may entail targeted investments in firefighting infrastructure, training, and the establishment of rapid-response teams to effectively manage and contain fires when they occur.

The clustering approach provides a spatially explicit framework for developing and implementing tailored fire prevention and management strategies. By identifying the unique characteristics of each cluster, policymakers can prioritize resource allocation, deploy targeted interventions, and encourage community engagement more efficiently and effectively. This can lead to a more holistic and proactive approach to fire mitigation, ultimately reducing the environmental and socio-economic impacts of forest and land fires in West Kalimantan.

The results of clustering hotspots using the KDE method with the Gaussian kernel function are then mapped. Mapping aims to visualize the level of forest and land fire vulnerability in West Kalimantan Province in 2020 using a geographic information system based on the global georeferencing system location (latitude and longitude) of each data member of each cluster. The map of forest fire risk areas is shown in **Figure 6**.

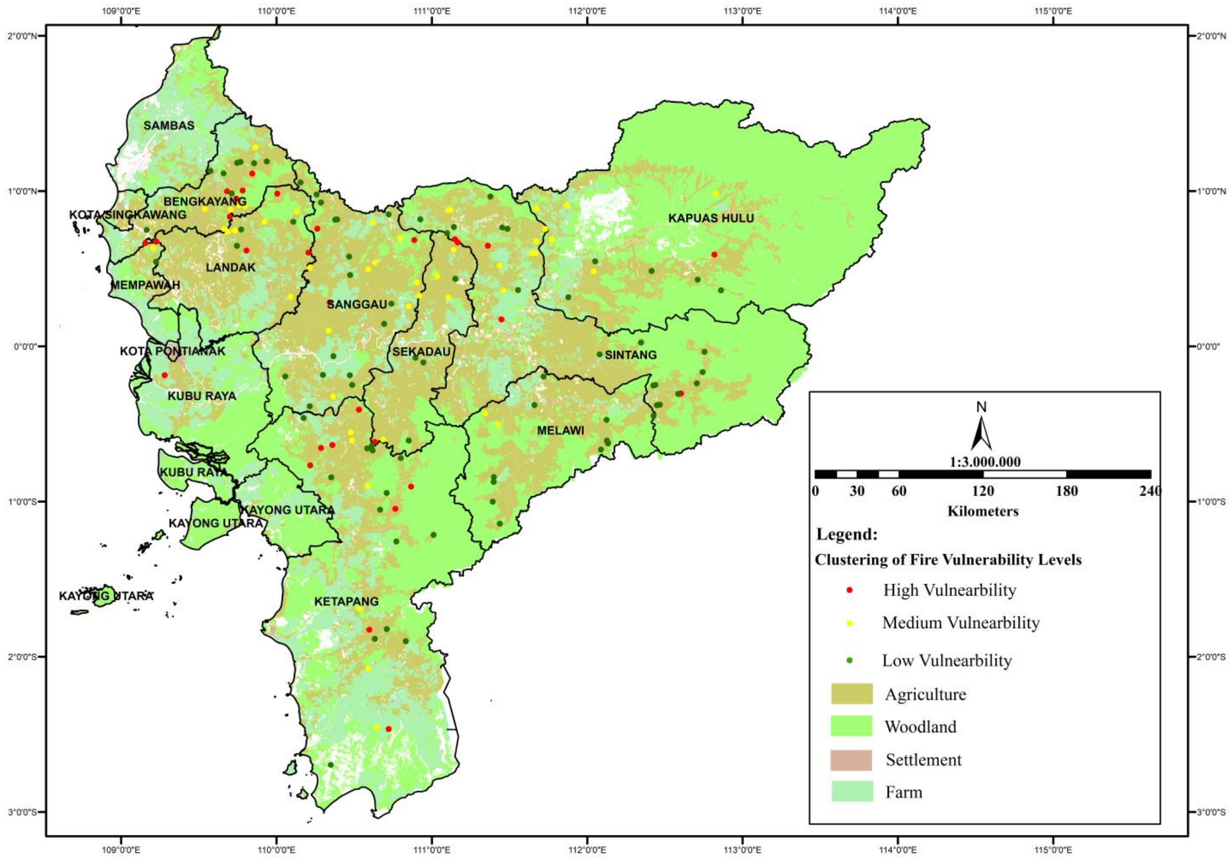


Figure 6. Forest Fire Risk Map in West Kalimantan

According to **Figure 6**, in areas with low vulnerability marked with green dots, there are 79 hotspots spread across 44 subdistricts and 9 regencies in West Kalimantan. With a total of 17 hotspots, Sintang Regency has the highest number of hotspots with a low vulnerability class. The medium vulnerability area marked with yellow dots consists of 47 hotspots spread across 33 subdistricts and 9 regencies in West Kalimantan. The number of hotspots with medium vulnerability is highest in Sanggau Regency, with 10 hotspots. Meanwhile, the high vulnerability area marked by the red dots consists of 29 hotspots spread across 25 subdistricts and 8 regencies in West Kalimantan. The highest number of hotspots in the high vulnerability class is found in Ketapang Regency, with 9 hotspots. Areas with dryland agricultural land mixed with shrubs dominate the hotspots with low, medium, and high vulnerability. This suggests that human activities are the cause of hotspots in West Kalimantan.

Therefore, the mitigation of forest and land fires can be done by conducting socialization and increasing awareness in the community. The government can conduct routine monitoring of forests and land to detect and prevent potential fires and make policies that prohibit activities that can cause forest and land fires, such as illegal logging, open burning, and other regulations related to the prevention of forest and land fires that aim to minimize the impact wildfires on land and in forests. Additionally, they can conduct research and studies on forest and land fire characteristics and perform risk analysis of such fires.

4. CONCLUSIONS

The analysis of forest and land fires in West Kalimantan led to the identification of three clusters through the use of KDE. Each cluster is distinguished by unique characteristics that provide valuable insights into the distribution and intensity of fires in the region. Cluster 1 was identified as an area with hotspots with low vulnerability, cluster 2 with medium vulnerability, and cluster 3 with high vulnerability. This approach can be employed as a mitigation method to minimize the impact of losses due to forest and land fires in West Kalimantan Province. Further research can be conducted to assess the effectiveness of mitigation strategies based on the clustering results, as well as to investigate other analytical approaches that can improve our understanding of fire patterns and dynamics in the region. However, it is important to note that the patterns of these fires can vary considerably based on seasonal conditions, especially the dry season. By considering the seasonal and annual variations in the occurrence of hotspots, this analysis can provide more comprehensive and targeted recommendations for the prevention and management of forest and land fires in West Kalimantan.

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