

# Spatial Distribution Patterns Analysis of Hotspot in Central Kalimantan using FIMRS MODIS Data

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**Abstract.** *One of the ways to observe the hotspot created by forest fires in Indonesia is through Remote sensing imagery, such as MODIS, NOAA AVHRR, etc. Central Kalimantan is one of the areas in Indonesia with the highest hotspot data. In this research, MODIS FIRMS hotspot data in Central Kalimantan collected from 2017 – 2019, covering 13 districts: South Barito, East Barito, North Barito, Mount Mas, Kapuas, Katingan, Palangkaraya City, West Kotawaringin, East Kotawaringin, Lamandau, Murung Raya, Pulang Pisau, Seruyan, and Sukamara. That is four aspects that this research evaluated: 1) evaluating the spatial pattern using the Nearest Neighbor Analysis (NNA); 2) evaluate the hotspot density appearance using Kernel Density; and 3) correlation analysis between rainfall data and MODIS FIRMS. As a result, the hotspot in Central Kalimantan shows a clustered pattern. While the natural breaks KDE algorithm shows the most relevant result to represent the hotspot distribution. Finally, the hotspot is low correlated with rainfall; however, is see that most of the hotspot (~90%) appeared in low rainfall month (less than 3000 mm/month).*

**Keywords:** *Forest fire, Hotspot, NNA, Kernel density, Central Kalimantan*

## 1. Introduction

Based on the Forestry Regulation of Indonesian Ministry for Environment No. P.12 / Menhut-II / 2009 Concerning Forest Fire Control Article 1, hotspots are indicators of forest fires that detect a location that has a relatively higher temperature compared to the surrounding temperature (Kehutanan, 2009). Wildfires in Indonesia, which are repeated from 1982 to 2019, have harmed the Indonesian people themselves. Cause the negative impact on the health, social, and economic life of the people in the surrounding areas. Brown and Davis stated that forest fires occur because of the rapid reaction process of oxygen with other supporting elements and have the characteristics of heat, light, and flame with free distribution caused by fuel in the form of vegetation, litter, humus, bushes, and weeds (Brown & Davis, 1973). Forest fires are influenced by natural (biophysical) factors, including fuel, climate, and topography, and human behavior factors include intentional actions such as land preparation by slash and burn, negligence to put out the fire. As the two statements above, we can conclude, a forest fire is one of the big problems that harm society in various sectors of life both for humans themselves and the life of plants and animals in the forest. Furthermore, forest and land fires can be detected by the presence

of hotspots obtained from MODIS (Terra / Aqua) satellite data (Davis, Yang, Yost, Belongie, & Cohen, 2017).

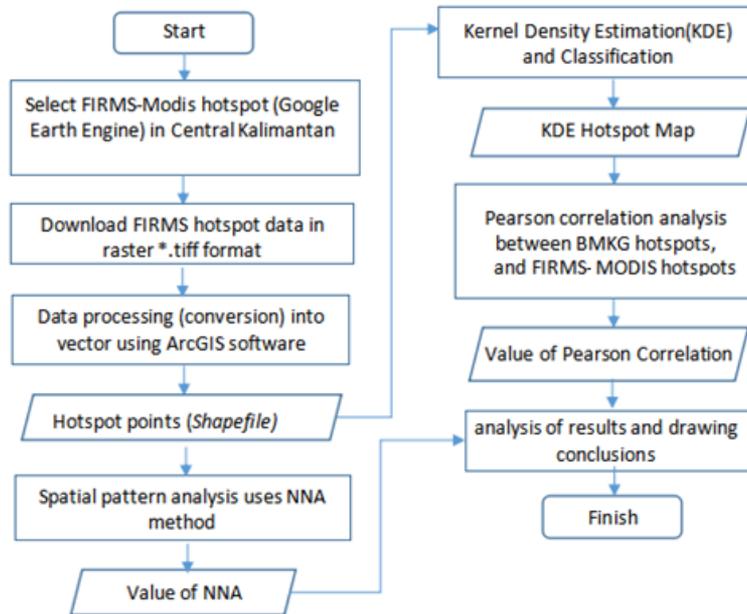
The effective ways to identify the forest fire is by using remote sensing imagery, namely, MODIS, NOAA, Landsat, etc. However, remote sensing imagery is limited to spatial and temporal resolution. The MODIS imagery is the most suitable imagery for identifying the forest fire due to the daily temporal resolution (Davies et al., 2019). Number of publication has implied the MODIS data for monitoring hotspot phenomena (Albar, Jaya, Saharjo, Kuncahyo, & Vadrevu, 2018; Davies et al., 2019; Endarwati, 2016; Sabani, Rahmadewi, Rahmi, Priyatna, & Kurniawan, 2019; Vetrira & Haryani, 2012; Wickramasinghe, Wallace, Reinke, & Jones, 2018; Zubaidah, Vetrira, & Khomarudin, 2014) and show the importance of MODIS imagery for hotspot identification.

Central Kalimantan is one of the provinces in Indonesia with a high level of forest fires. This is supported by data from the Ministry of Environment and Forestry in the Forestry and Land Monitoring System at <http://sipongi.menlhk.go.id/hotspot/> that from 2014 to 2019, the area of the highest forest fires in Indonesia reached 777,408.1 hectares located in Central Kalimantan Province. Even several publication have tested the MODIS data (Alfandy, Tahmid, & Sari, 2017; Sabani et al., 2019; Sumarga, 2017) or other remote sensing imagery (Aflahah, Hidayati, & Hidayat, 2019; Putra, Hayasaka, Takahashi, & Usup, 2008) in Central Kalimantan, however for the first time in this study a spatial pattern analysis is used. In addition, how the relationship between forest fires and their causes from natural factors namely rainfall is interesting to analyze. Fuller states that the weather aspect including temperature, humidity, rainfall, wind, and air stability directly influences the potential for forest fires appearance (Fuller, 1991).

## 2. Materials and Methods

This research uses quantitative and descriptive analysis methods. Quantitative and descriptive analysis methods emphasize objective measurements and the statistical, mathematical, or numerical analysis of data. The types of spatial data varied depending on their usefulness. For example, point data is used to represent the location of forest fires while area data is used to represent socio-economic statistical data and demographic characteristics. The complexities may be aros when correlating a data type with other data in statistical comparisons and analyses (De La Riva, Pérez-Cabello, Lana-Renault, & Koutsias, 2004). Interpolation is a method for predicting attribute values at locations that are not sampled from observational data samples in the study area and can be used to convert data from observation points into continuous data. However, some methods require variables to estimate a location function. In contrast, Kernel Density Estimation (KDE) can be used as an interpolation technique for individual observation points. This approach was developed as an alternative method in achieving a smooth univariate or multivariate probability density function of an observation sample such as a histogram (De La Riva et al., 2004).

In this paper we use rainfall, and FIRMS MODIS hotspots data. The stages of this research are: (1) Selecting FIRMS-Modis hotspot data through Google Earth Engine. (2) Downloading FIRMS hotspot data in raster \*.tiff format. (3) Then processing data using ArcGIS software, namely raster data conversion into \*.shp (shapefile) vector format. (4) Through ArcGIS, Nearest Neighbor Analysis (NNA) values can be calculated to see the spatial pattern of hotspots in Central Kalimantan. (5) analyze and classified the hotspot probability based on Kernel Density (KDE) method. (6) Next do the Pearson correlation analysis to find out how the correlation between BMKG rainfall data, and FIRMS-MODIS hotspots. (7) The final step is the analysis of results and drawing conclusions. The research flow can be seen in Figure 1.



**Figure 1.** Flowchart

## 2.1. Materials

### 2.1.1. Rupa Bumi Indonesia Map (National Basemap)

Feature of Central Kalimantan Administrative Boundary based on *Rupa Bumi Indonesia Map* Scale 1:50.000 the year 2017 obtained from Geospatial Information Agency. The administrative layer on *Rupa Bumi Indonesia Map* (National Basemap) is used to select FIRMS hotspot data and to present analysis maps.

### 2.1.2. Dataset Fire Information for Resource Management System (FIRMS)

Hotspots based on Fire Information for Resource Management System (FIRMS), MODIS is collected using the Google Earth Engine portal which addresses <https://earthengine.google.com/>. Gorelick (2017) states that Google Earth Engine is a cloud-based platform for geospatial analysis that brings Google's massive computing capabilities to deal with variations in social impact issues including deforestation, drought, disaster, water management, climate monitoring and environmental protection (Gorelick et al., 2017). This data is near-real-time (NRT) of active fire locations processed using LANCE with MODIS MOD14 / MYD14 Fire and Thermal Anomalies product standards. Hotspot selection based on Band T21, where the occurrence of hotspots in the temperature range of at least 325 - 400 Kelvin. Each active fire location represents the centroid of 1 Km pixel marked by an algorithm that contains one or more fires in pixels. Data rasterization for each active FIRMS hotspot, defined bounding box (BB) 1 Km, pixels on the sinusoidal projection MODIS that intersect with FIRMS, BB is identified; if there are several FIRMS, BB intersect with the same pixel, the highest confidentiality is maintained; if there is one series, the brighter is maintained. FIRMS-Modis Hotspots collected from earth engine platforms are saved in raster format, to apply the NNA analysis the data should be converted into vector shapefile. The hotspots vector for Central Kalimantan in 2017-2019 there is 54,246 points.

### 2.1.3. Rainfall Data

Rainfall data in this study is monthly rainfall in Central Kalimantan with millimeters (mm) unit, from 2017 - 2019 obtained from the BMKG. Rainfall or precipitation means the amount of rain falling in a certain area in a certain time unit. The amount of rainfall is the volume of water collected on a flat

surface in a certain period (daily, weekly, monthly and yearly). Rainfall is measured in millimeters (mm) above the horizontal surface.

2.2. Methods

2.2.1. Nearest Neighbor Analysis

The ANN calculates the distance between each feature centroid and its neighbor centroid location. It then averages these entire nearest neighbor distances. If the average distance is less than the average for a hypothetical random distribution, the distribution of the analyzed features is considered clustered (ESRI, 2020). If the average distance is greater than a hypothetical random distribution, the features are considered dispersed. R calculates the distance between one case to its nearest case and was calculated using the equation below (Moore & Carpenter, 1999):

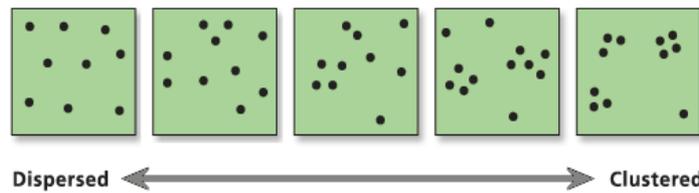
$$R = r_{obs} / r_{exp} \dots\dots\dots (1)$$

where  $r_{obs}$  is the observed average distance between nearest neighbours and  $r_{exp}$  is the expected average distance between nearest neighbours as determine by theoretical pattern being tested.

$$r_{obs} = \Sigma \{ \text{Min} (d_{ij}) / N \}$$

$$r_{exp} = \sqrt{A/N}$$

where  $\text{Min} (d_{ij})$  is the distance between each point and its nearest neighbour, A is the area of the space of concern and N is the number of points in the distribution. The R value that is less than 1 indicates that the distribution is clustered and value more than 1 indicates that distribution is dispersed or uniform. If the value is totally equal as 1, it indicates random distribution pattern.



**Figure 2.** Illustration of spatial distribution (ESRI, 2020)

2.2.2. Kernel Density Estimation

The kernel density is a non-parametric method that uses a density estimation technique. This method enables the observer to evaluate the local probability accident occurrence and degree of danger of a zone (Manepalli, Bham, & Kandada, 2011). From an unknown probability density function of a given set of observations, the function of Kernel estimator can be defined as (Manepalli et al., 2011):

$$p = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - X_i}{h}\right) \dots\dots\dots (2)$$

where K is a weighting function. This function does is providing a smart way of estimating the density in x, by counting the frequency of other points  $X_i$  in the same bin as x and weighting them differently depending on their distance from x. Contributions to the density value of f in x from points  $X_i$  vary, since those that are closer to x are weighted more than points that are further away. This property is fulfilled by many functions, that are called kernel functions. A kernel function K is usually a probability density functions that integrates to 1 and takes positive values in its domain (Biba, Esposito, Ferilli, Di Mauro, & Basile, 2007).

Kernel Density Estimation (KDE) is carried out to determine the probability of a hotspot event where this method is a non-parametric statistical method that has been widely used (Erran Seaman &

Powell, 1996). When implementing Kernel interpolation, each active hotspot is considered not as the exact location of the point but rather as an uncertain point that defines a wider surrounding than the actual point (De La Riva et al., 2004). Kernel mapping is obtained based on the assumed density distribution for each sample point. The density distribution is placed in the sample plane, one for each observation point, and added vertically to get the composite density of the sample. This composite density is used to identify core areas and determine densest areas (Bolstad & Eider Press, n.d.). Hart and Zandbergen states Kernel Density can be classified by several different methods to define hotspots, including equal intervals, natural breaks, manual intervals, and standard deviations (T. Hart & Zandbergen, 2014), describe as follows :

- a. Equal Intervals: In the equal interval schemes, the classification is identified hotspot clusters and we can make a comparison between different daily KDE maps (Silverman, 1986)
- b. Natural Breaks: In the natural breaks scheme, the classes are based on natural categorizing inherent in the data (Manepalli et al., 2011).
- c. Standard Deviations: In Hotspot analysis, users need only to define the study area and the features being analyzed, when the analysis includes the size of the search radius, the units in which the search radius is based, the minimum number of points that define a cluster, the number of simulations that will be run. The type of scanning procedure (e.g. rectangular or triangular), and the number of standard deviations used to create the output ellipses (Bates, 1987; Canter, 1993; Spring and Block, 1989 in T. C. Hart, 2020).

Classification of data by looking at spatial patterns of spreading points whether clustered or random and comparing each map of KDE results.

### 2.2.3. Pearson Correlation

Pearson  $r$  correlation is one of most widely used correlation statistic tools to measure the degree of the relationship between linearly related variables (Zou, Tuncali, & Silverman, 2003). The point-biserial correlation is conducted with the Pearson correlation formula except that one of the variables is dichotomous. The formula for computing  $r$  between bivariate data,  $X_i$  and  $Y_i$  values ( $i = 1, \dots, n$ ) is (Zou et al., 2003):

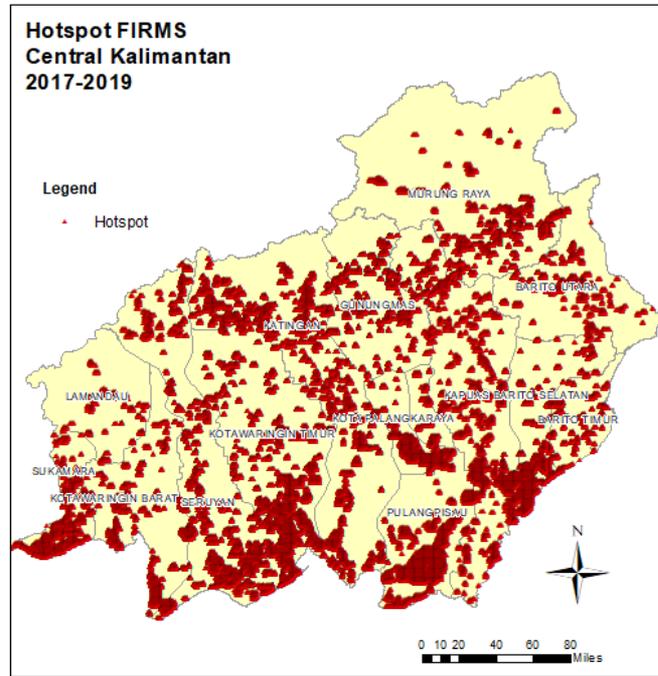
$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}}, \dots\dots\dots (3)$$

where  $X$  and  $Y$  are the sample means of the  $X_i$  and  $Y_i$  values, respectively.

## 3. Results and Discussion

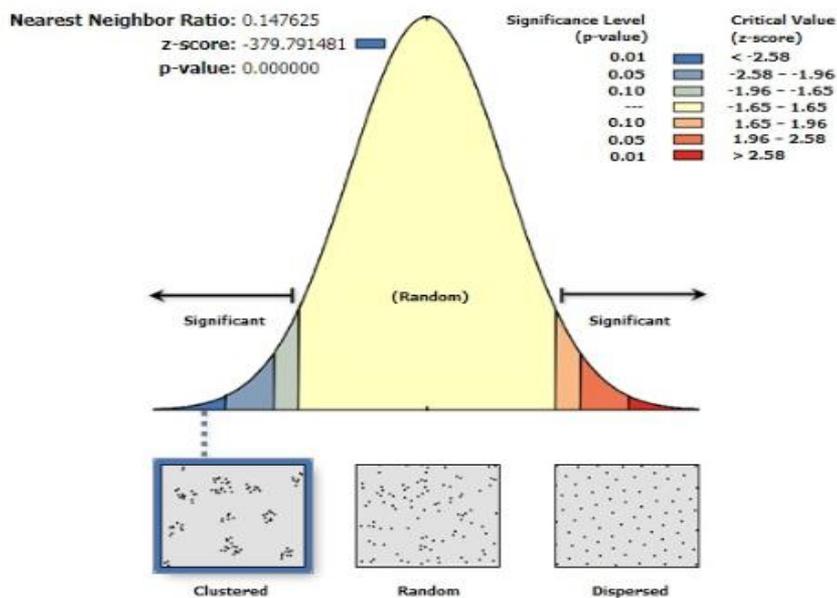
### 3.1. The pattern of hotspots distribution based on NNA Analysis

Based on visual interpretation in Figure 3, it can be seen that the tendency of hotspots' pattern is getting denser in the middle to the south, and less frequently in the north. Based on this hotspot data, NNA analysis is performed to determine detailed spatial distribution patterns. The detail results of NNA calculations based on ArcGIS is shown in Figure 4. The analysis displays that the value of the NNA ratio ( $R$ ) is 0.147 and indicates the significant negative value of the critical zone. This means that the hotspot incident in Central Kalimantan has a clustered distribution pattern. This is consistent with the visual interpretation that is mentioned earlier.



**Figure 3.** Central Kalimantan Hotspot Point Map Based on FIRMS Data, Modis

Further, the clustered pattern of Hotspot in Central Kalimantan became one of the proofs that the phenomena do not happen naturally or said as artificially human-made. Emphasize by several past studies that show forest fire has a strong relation with human influence (Sumarga, 2017; Turmudi, Yustisi, Riadi, Suwarno, & Purwono, 2018). Furthermore, the human-made hotspot mostly appears in the peat area, and oil palm plantation (Turmudi et al., 2018).

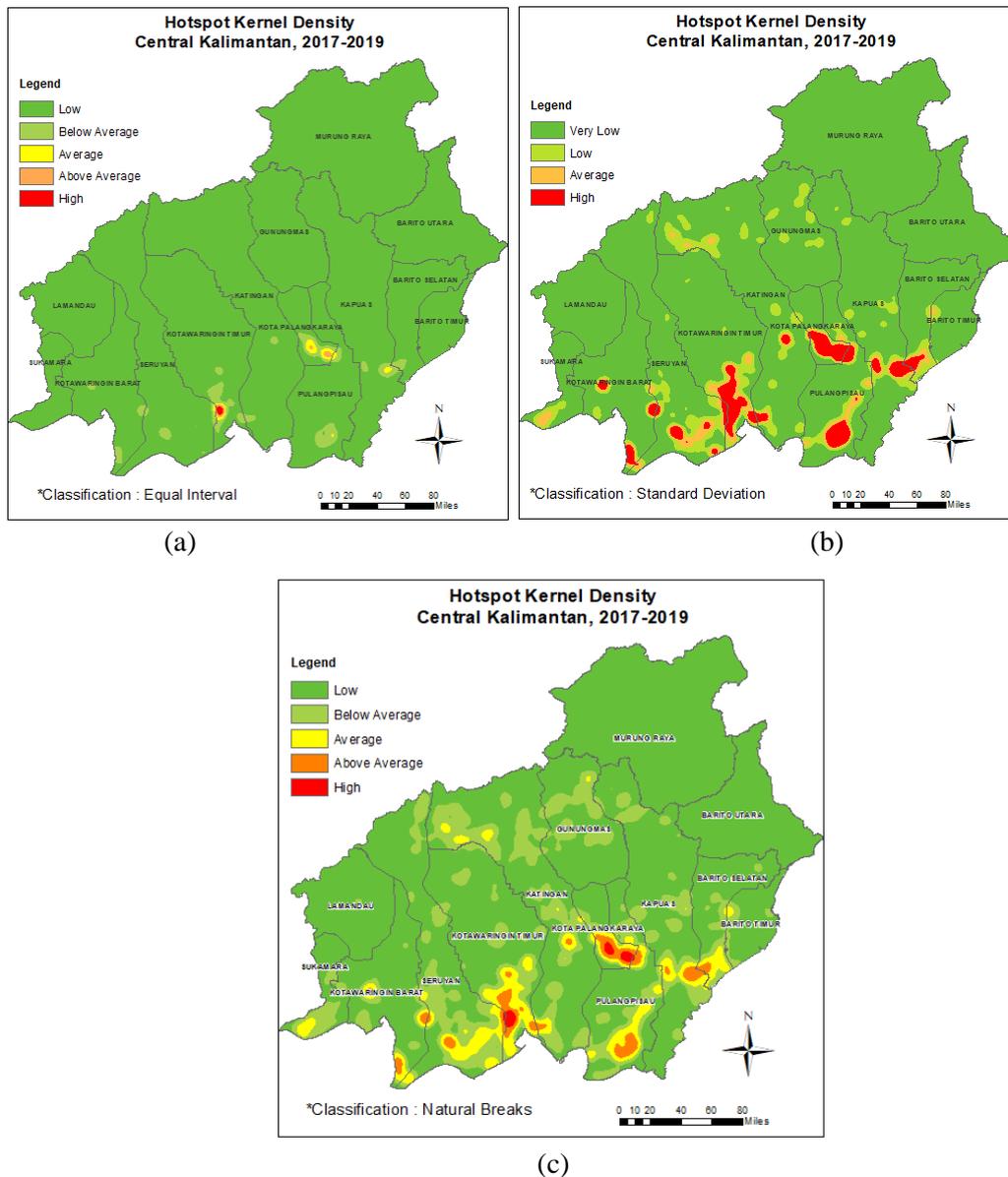


**Figure 4.** Average Nearest Neighbor Ratio Graph

### 3.2. The pattern of hotspots distribution based on Kernel Density Analysis

Figure 5 displays the results of the classification of Hotspot density using the Kernel Density algorithm with three options, namely Standard Deviation, Equal Interval, and Natural Breaks. The results of the three classifications show significant differences in the Equal Interval method and can be declared

unsatisfactory to see the risk level of a hotspot. The results of the classification of this method indicate that the Central Kalimantan region has a very low risk of hotspots and that in Central Kalimantan there is no sizeable visible area for medium, high, and very high hotspots. As for the classification using the first method, the results of Standard Deviation and Natural Breaks are almost similar, but the division of 5 classes Natural Breaks is better in showing the hotspot risk area in detail for each class. This is caused by the division of classes in the Natural Breaks classification considers uniform class ranges.



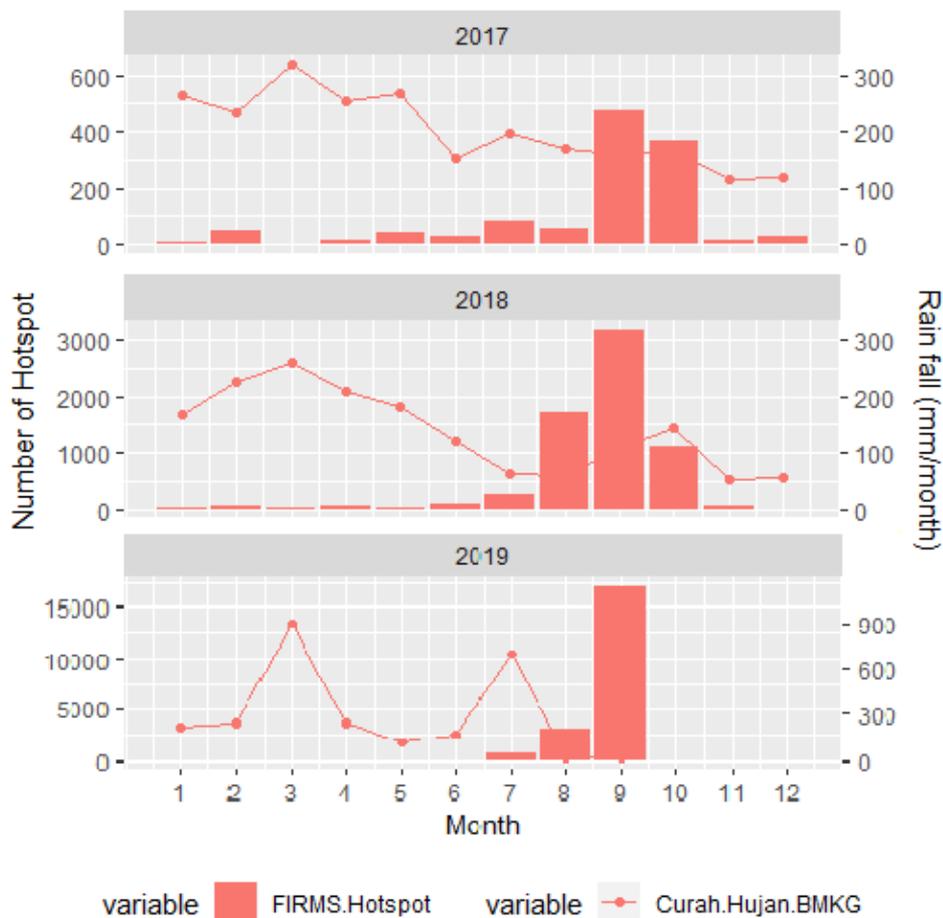
**Figure 5.** Classification of Kernel Density Analysis (a) Standard Deviation (b) *Equal Interval* (c) *Natural Break*

KDE hotspot map classification based on the Natural breaks method is divided into five classes, very low, low, medium, high, and very high. At some districts in Central Kalimantan, especially in the middle to the south tend to be a moderate risk to very high. The highest hotspot areas are in the East Kotawaringin and Palangkaraya City. At Kotawaringin Timur District, the high risk includes the Districts of South Mentaya Hilir, North Mentaya Hilir, and Teluk Sampit. While for the City of Palangkaraya, especially in the District of Sabangau, Jekan Raya, Sabandut. In the middle to the north

in the region of Central Kalimantan has a moderate- very low probability, but it is dominated by dark green which displays a very low probability.

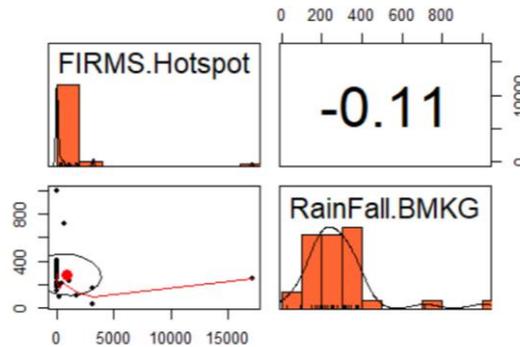
### 3.3. The Correlation between HOTSPOT and Rainfall

In this study, the correlation between the number of MODIS FIRMS hotspots data compared with BMKG.rainfall data as shown in Figure 7. The average rainfall is varied in each year ranging from 50 – 1000 mm/month. While the number of Hotspots is also appeared differently in each year, from 7 – 18.000. The trend of the growth of hotspots began to emerge in July - October. This can be due to the peak of the dry season, the slight rainfall triggered by high temperatures triggers the growth of hotspots. Moreover, it can be seen that the highest peak of Hotspot emergence during 2017-2019 is happening in July - September 2019, which is following the lowest rainfall data for that year and also recorded as the highest number of hotspots since 2015 forest fire. The one-month forest fire event in September 2019 find to be equal with the entire year hotspot of 2018 (“Area burned in 2019 forest fires in Indonesia exceeds 2018 - official - Reuters,” n.d.).



**Figure 7.** Graph of Hotspots monthly from FIRMS and BMKG data and rainfall

The relation between rainfall and hotspot is analyzed using Pearson Correlation. This study shows a correlation between the number of hotspots from FIRMS hotspot data compared with rainfall data from BMKG. Figure 8 shows that the Pearson correlation value shows a low correlation (0.47). Rainfall commonly used to indicate the number of the forest fire, however, in this study, the assumption is not proven. This result is fit with the previous study that evaluates climate factor (rainfall, temperature, etc.) with the appearance of the hotspot (Aflahah et al., 2019). Moreover, still, the high number of hotspots is shown when rainfall is low.



**Figure 8.** Pearson Correlation Graph

#### 4. Conclusion

This study examines the spatial pattern of FIRMS hotspot data accesses from Google Earth Engine and the correlation with hotspot data published by BMKG. The findings from this study are summarized as: 1) The spatial pattern analysis using the NNA method shows that the Central Kalimantan region has a clustered pattern of hotspots distribution; 2) Kernel Density analysis results show highest hotspots area in East Kotawaringin, Palangkaraya City, and Pulang Pisau; 3) Based on Pearson correlation analysis between the number FIRMS hotspots, and BMKG rainfall shows low correlation. However, the peak hotspot data occurs mostly in the Dry Season (June - October), this is due to the minimal rainfall during the dry season which makes atmospheric humidity conditions dry, potentially increasing the temperature conditions in the forest which can trigger the emergence of hotspots.

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