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Research Paper

Hotspot Distribution Analysis In East Kalimantan Province 2017-2019 to Support Forest and Land Fires Mitigation

Nurwita Mustika Sari [1,2]*, Nurina Rachmita [1], Masita Dwi Mandini Manessa[1],

[1] *Department of Geography, Faculty of Mathematics and Natural Science, Universitas Indonesia*
[2] *Remote Sensing Applications Center, LAPAN*
***Corresponding author e-mail**: nurwita.mustika@lapan.go.id*

Abstract
Forest and land fires that have occurred in the territory of East Kalimantan Province have caused immediate disaster to the area from year to year and become a global concern in recent years. Hotspots that potentially cause forest and land fires can be detected using satellites such as NOAA-20. The purposes of this study are to analyze the distribution pattern of hotspots in East Kalimantan Province during 2017-2019, identify areas with the highest risk of fires caused by the high intensity of hotspot. The method used in this study is the Nearest Neighbor Analysis and Kernel Density Estimation analysis. The results showed that the distribution pattern of hotspots in East Kalimantan Province during 2017-2019 was clustered with the highest intensity of hotspots were in Berau, East Kutai and Kutai Kartanegara Districts. And from the result of the analysis, the highest number of days has a peak hotspots on September each year.

Keywords
forest and land fires, hotspots, Nearest Neighbor, Kernel Density Estimation

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1. INTRODUCTION

Forest and land fires in several locations in Indonesia such as Kalimantan and Sumatra occur almost every year with larger areas and longer duration. The impact of this forest and land fires physically is a decrease in air quality due to thick haze, followed by the risk of respiratory diseases such as ISPA (Acute Respiratory Infection). Furthermore, on a global scale, the haze caused by forest and land fires, since the late 1990's, the impact was felt to reach Malaysia, Singapore and Brunei Darussalam (Rasyid, 2014). The movement of warm air masses and the effect on the weather around the fire area will trigger the spread of fire areas, especially during periods of active fires that require special attention (Hayasaka et al., 2019). Various kinds of losses caused by forest and land fires encourage all parties to make control effort so that similar incident will not recur, including suppressing the causes of forest and land fires from human factors (Tacconi, 2016).

A hotspot is a point in an area that is detected to have a higher temperature than the surrounding area that has the potential to cause forest and land fires (Permenhut Number P.12 / Menhut-II / 2009) . This hotspot can be identified in several ways including using NOAA or MODIS Terra and Aqua satellites. Detection of hotspots by other methods is the Extended Fuzzy C-Means (EFCM) method for large and very large data groups (Martino et al., 2018) and the use of the Extended Fuzzy C-Means Spatiotemporal algorithm (Martino and Sessa, 2018). Although every hotspot that is detected is not necessarily a fire, with a high level of confidence above 80%, this hotspot will help to identify the initial occurrence of forest and land fires so that it can help disrupt this disaster in the field (Endrawati, 2016). Previous studies have shown that hotspot data extracted from MODIS have the reliability to show areas that are actually burning (Hantson et al., 2013), however the user needs specifications continue to increase to how hotspots can inform carbon emission (Mouillot et al., 2014).

In this study, the analysis of the hotspots distribution will be conducted, where the purpose of this study was to determine the hotspot distribution patterns in the area of East Kalimantan Province during 2017-2019, identify areas with high risk of fire due to high intensity of hotspots and identify periods with the most hotspots. Previous research has been conducted to determine the pattern of point distribution including the analysis of the distribution of Dengue disease points using the Nearest Neighbor method and identify risk areas with Kernel Density Estimation (Santosa et al., 2018), analysis of distribution pattern of common crime and robbery points (Chen et al., 2010, 2012), for the health sector there were a spatial analysis of cancer cases (Shah et al., 2014), spatial analysis of diarrhea cases (Chaikaew et al., 2009), for the veterinary study (Ward, 2007). Kernel Density method has also been used to determine the tendency of data intensity with the form of data points in the school reference case (Adhi et al., 2019). Meanwhile for hotspot cases, hotspot distribution has been analyzed using the Kulldorff's Scan Statistics (KSS) method for peatland (Kirana et al., 2016) and hotspot analysis with Density-Based Spatial Clustering Algorithms with Noise (DBSCAN) (Usman et al., 2015). Meanwhile the correlation between hotspot and rainfall has been done by (Prayoga et al., 2017) with the result of sufficient correlation and negative relationship. For the distribution of hotspots, a spatial analysis was conducted for the Malaysian peninsula (Mahmud, 2017). However, the analysis of hotspot distribution patterns has not been conducted using the Nearest Neighbor Analysis method for the specific area of East Kalimantan province in the period of 2017-2019.

Meanwhile, to find out the period with the most number of hotspots, analysis was conducted to the hotspot data obtained from weather satellites, which are known to be the time span with the highest number of hotspots in an area (Zubaidah and Arief, 2004). The same thing was done in this study at East Kalimantan province as one of the provinces with the largest forest and land fires, even for the area of fire including ranks third in Indonesia (Endrawati, 2016), it is important to analyze the hotspots in this area so that disaster management planning and implementation in the field can be more effective.

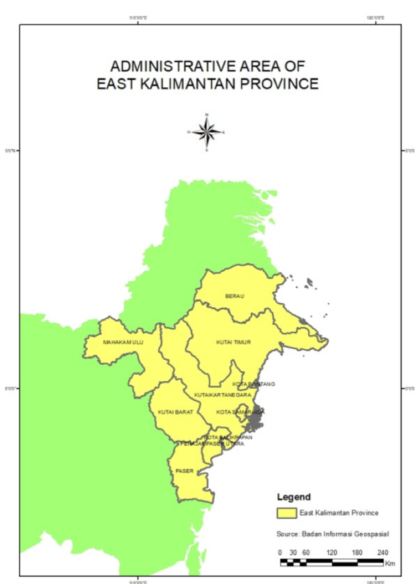

Figure 1. Study area of hotspot distribution analysis

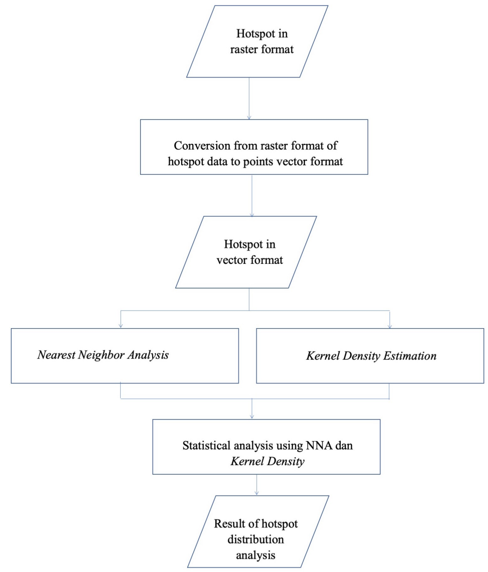

Figure 2. Flowchart of hotspot distribution analysis

2. EXPERIMENTAL SECTION

2.1 Material

The data used in this study are hotspot data obtained from NOAA-20 satellites since 2017-2019. Other data used is the administrative boundary data of East Kalimantan province obtained from Badan Informasi Geospasial (BIG). The study area is presented in Figure 1.

East Kalimantan province consists of 10 District / City including the District of Berau, Balikpapan, Kota Bontang, Kota Samarinda, Kutai Kartanegara, Kutai Barat, Kutai Timur, Paser, Penajam Paser Utara, Mahakam Ulu. Another data is settlement data in the study area obtained from BIG in 2015.

2.2 Method

The analysis of the distribution pattern of hostspot points in the study area was carried out using the Nearest Neighbor Analysis and Kernel Density Estimation methods and is presented in Figure 2. The stages of the research are:

- Pre-processing hotspot data
  Data pre-processing was carried out by extracting hotspot data from NOAA-20 satellites in the range of 2017 to 2019 using Google Earth Engine. Next step was selecting hotspot data for the study area, namely East Kalimantan Province. In processing hotspot data generated from NOAA-20 satellite data, the area of Mahakam Ulu Regency was included in the boundary of Kutai Barat Regency which was located next to Mahakam Ulu, because the administrative boundary used was the year before the regional expansion. However, the number of hotspots in Mahakam Ulu was still included in the analysis. Data raster that has been obtained was then converted to the format of

the vector points, after that the data with the new format of vector points were merged into single data East Kalimantan Province hotspots 2017-2019. This data was used for the next stage namely statistical analysis.

- Statistical analysis method
  Analysis of the data using Nearest Neighbor Analysis, an analysis that was used as one of the ways to explain the distribution pattern of the hotspots by using calculation which considered the number of points, total area and distance.
  The final result of this analysis is an index (Rn), the index value of NNA distribution. He formula:

$$D_{obs} = \frac{\Sigma d}{n} \tag{1}$$

$$Rn = 2D_{obs}\sqrt{\frac{n}{a}} \tag{2}$$

where, Rn = Nearest Neighbour Index; Dobs = The average distance between the closest points; d = Distance between the closest points; N = Total points; A = Width
Criteria :

Analysis of Kernel Density using interpolation of points distribution with the grid based distribution of hotspot to estimate the intensity through the calculation of the amount which is detected in a specific area.

The hotspots in East Kalimantan region were analyzed by Kernel Density analysis. For a random set of data with variables x1, x2, x ..., xn, the estimated Kernel Density to see the density probability is:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{3}$$

where, K is a kernel function and has several types, but the most commonly used is the normal function , K = 0.399 exp (-0.5u 2) (Chen et al., 2010).

3. RESULTS AND DISCUSSION

Program codes that were runned on the Google Earth Engine obtained results in the form of raster format containing hotspots and a CSV format file. The data in raster format subsequently converted into vector point format. The result is hotspots distribution in East Kalimantan province with

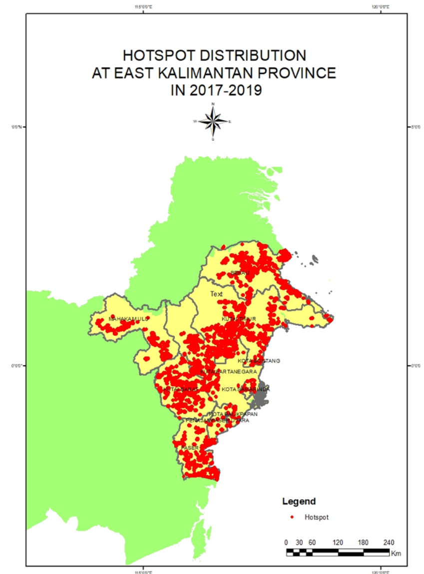

Figure 3. Distribution of hotspots in East Kalimantan 2017-2019

time span of three years from 2017 to 2019. It can be seen in Figure 3, the hotspots spread in all districts/ cities.

Nearest Neighbor Analysis (NNA) summary result shows the pattern distribution of hotspot in East Kalimantan with the NNA indexes as shown in Figure 4.

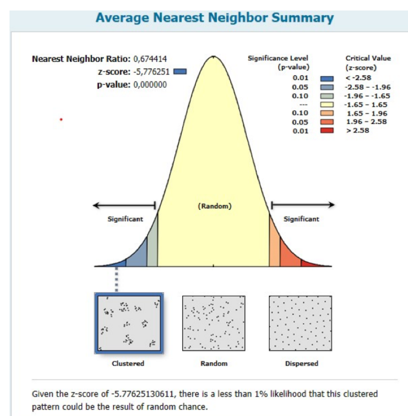

Figure 4. NNR values in the ArcGis application

Nearest Neighbor Ratio or NNR is 0.674414 and the Z-score is -5,77. With the provision of criteria which has been described previously, it can be interpreted that the hotspot pattern in the region of East Kalimantan is clustered.

Analysis using Kernel Density Estimation was carried out to find out how the intensity of the distributed hotspots and represented in the form of .tif raster data format. The result of raster data was then overlayed with administrative boundary as shown in Figure 5.

From the result of the Kernel Density Estimation, it can be seen that the areas that were detected with the highest

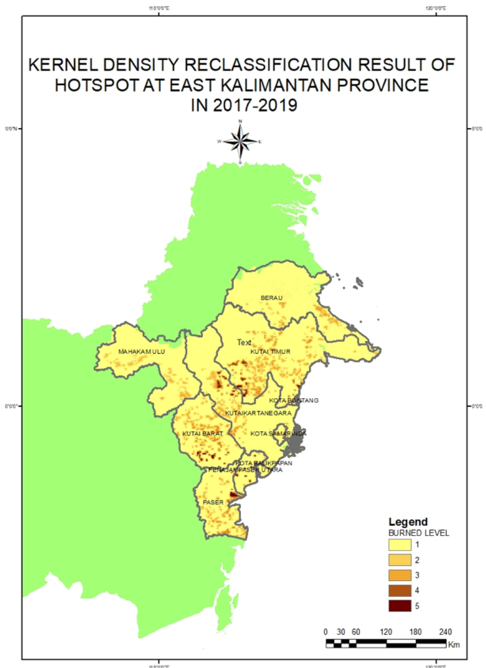

Figure 5. Kernel Density analysis results

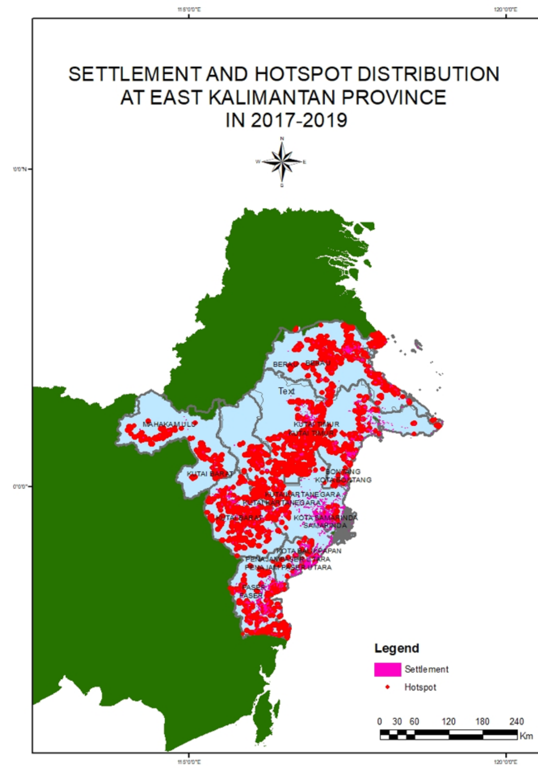

Figure 6. Overlay settlements with hotspots

number of hotspots have value of the highest rank namely 5. From the legend, it is showed that areas with the highest intensity of hotspots have the darkest color, while the areas of the rarest hotspots have the lowest value namely 1 and have brightest color. It can be interpreted that the most intensity of the hotspots in an area, then the color will be more intensive.

The next result is the overlay between settlement and hotspots map. From the picture below it can be seen that the settlement residents quite close to the hotspots, of course, the incidence gives the effect of which is detrimental to the citizens, especially the thick haze problem arising from the forest and land fire event. The impact of the incident is such, the worse quality of air even up to the level of danger and decrease the visibility. Another that, it caused the eye wound and acute respiratory infection (ISPA).

Based on the map of the Ministry of the Environment Life and Forestry in 2019 (Figure 7) , the use of land in the region of East Kalimantan, consists of regional asylum nature/ conservation of nature, conservation of water, protected forest, limited production forest, permanent production forest, production forest that can be converted and other land uses (settlement, rice field, swamp, field, etcetera). Hotspots in East Kalimantan most substantial occurs in the protected forest, limited production forest and permanent production forest.

Analysis of the number of days indicated the existence of a hotspots. From the output CSV file, it can be obtained the number of days with the number of hotspots in every month during the last 3 years (Table 8). The region, which has the most number of days of hotspots in 2017 and 2019 is Berau, and for 2018 is Kutai Kartanegara. Areas with number of hotspots are Berau, Kutai Timur and Kutai Kartanegara. From the following table it can be concluded that the highest number of days with the peak period of hotspots were in August and September in every year.

Based on these figures (Figure 9-11), it can be seen that the number of days at the beginning of the year is still at a low level. The emergence of hotspots began to show an increase in July to reach the peak in September. This is considered to be related to the dry season which reaches its peak in August or September, causing the observed hotspots to reach their maximum. Furthermore, in the following month namely in October the number of hotspots has decreased due to climatic conditions began to enter the rainy season again. This pattern is repeated every year.

Besides this, the emergence of high hotspots in August related to the agricultural activities of the community of Kalimantan. The agricultural system that is usually applied in the Kalimantan region is an extensive farming system, including the use of land prepared by burning of rice plants. Rice plants are usually done before the rainy season around September, while land preparation is done one month before, namely in August. The land preparation activity can trigger the emergence of hotspots as an indication of forest / land burning activities.

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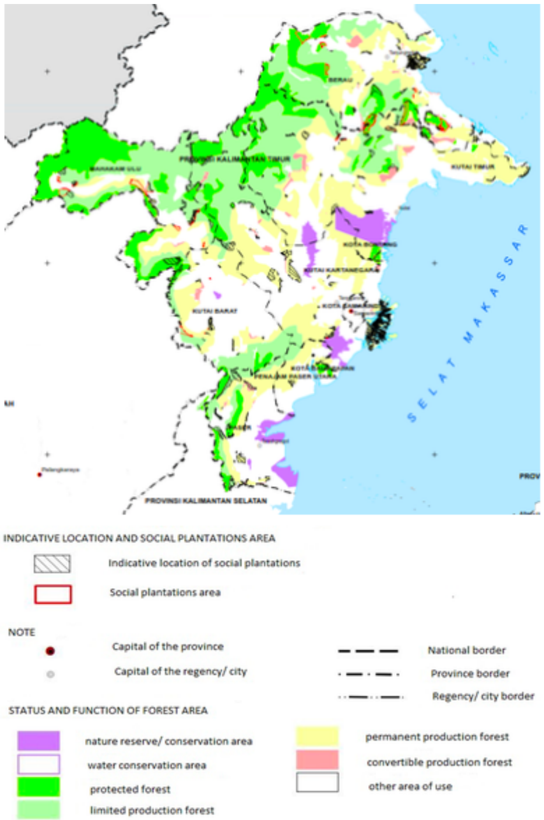

Figure 7. Land use in East Kalimantan Province 2019

Regency/City	Year	Month												The Number of days
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Berau	2017	2	1	2	5	11	6	7	7	13	7	2	2	65
	2018	1		4	4	11	4	5	13	14	12	4	4	76
	2019		4	10	11	9	9	13	25	16				97
Balikpapan	2017		1								2	1		4
	2018				1					2				3
	2019								2	1				3
Bontang	2017		3	1		1	3	1	2		1			12
	2018	1		1	1	2		1	1	2	1	2		12
	2019		5	3	1		1	1	3	4				18
Samarinda	2017				1	1			1	1				4
	2018					1		2	1	1				5
	2019		1		3	1		1	1	2				9
Kutai Kartanegara	2017		1	1	4	6		4	11	9	8	2	4	50
	2018	1	1	4	5	3	6	9	13	20	11	4	7	84
	2019	2	12	11	4	6	2	8	14	15				74
Kutai Barat	2017				1				6	12	9		2	30
	2018			1	1	4	1	4	16	16	12	5	2	62
	2019	4	12	5	1	2	1	5	13	13				56
Kutai Timur	2017	1	1		6	9	3	7	3	10	8	1	1	50
	2018	1	3	3	2	6	3	5	14	20	11	11	8	87
	2019	7	13	10	7	5	6	7	18	14				87
Paser	2017		1	1	1	1	2	2	2	7	6		1	24
	2018	1	2	2	3	5	2	2	5	13	9	3		47
	2019	1	1	1	2	1	2	4	11	13				36
Penajam Paser Utara	2017					1				1	2			4
	2018							1	1	3	2			7
	2019	1		1	1					4				7

Figure 8. Table number of hotspots days

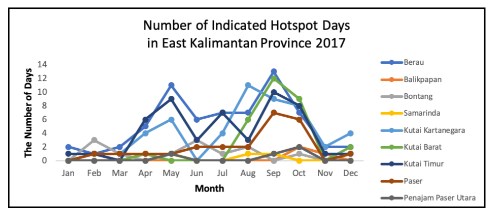

Figure 9. Charts in 2017

4. CONCLUSIONS

Based on the hotspot data processing of the East Kalimantan province in 2017 - 2019, it is indicated that there were highest hotspots in Berau, Kutai Timur and Kutai Kartanegara. From the result of the analysis using the Nearest Neighbor Analysis (NNA), the distribution of hotspots in East Kalimantan province was clustered.

While the result of the highest number of hotspots days, the peak was in of September in each year. Pattern of hot spots and related with the rainy season could be a recommendation in preparing the disaster management strategy of forest and land fires in Indonesia. Preparations for the thick haze and smoke disaster management due to forest and land fires such Weather Modification Technology is better prepared before the dry condition reaches the peak.

5. ACKNOWLEDGEMENT

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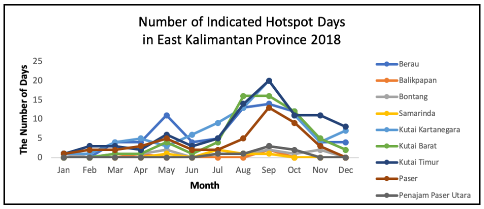

Figure 10. Charts in 2018

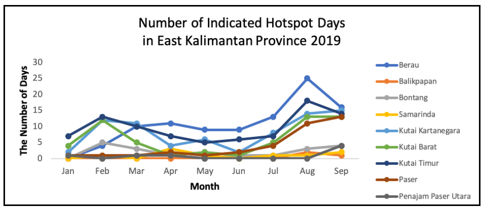

Figure 11. Charts in 2019

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