

Correlation of drought and fire hotspots by using Standardized Precipitation Index (SPI) from TRMM Rainfall Data from 2015 to 2019 at Central Kalimantan, Indonesia

M Ihsanur Adib, Muhammad Wisnu H, Zulfa Andriansyah

Geographic Information Science Department, Faculty of Geography, Universitas Gadjah Mada, Sekip Utara, Bulaksumur, Yogyakarta

Email: ihsanuradib@mail.ugm.ac.id; muhammad.wisnu@mail.ugm.ac.id ;
zulfaandriansyah@mail.ugm.ac.id

Abstract: Kalimantan is a region in Borneo Island in Indonesia that holds a massive tropical forest with 36.5 million ha, which covers 30,2% of the national forest area. More importantly, the tropical forest in Kalimantan is mostly covered by peatlands at risk of forest fires. Historical data showed that most of the fire events happened in Central Kalimantan. According to the Indonesian Ministry of Environment and Forestry, around 22,35% of burned forest areas in Indonesia during 2015 forest fire cases happened in Central Kalimantan. While in the 2019 Indonesian forest fires, around 19,26% of burned forest areas also happened in Central Kalimantan. One of the leading causes of forest fires is the dryness of peatland that the lower part of it is incredibly prone to be a source of the fire. This heat source, called fire alerts, can be seen using thermal-based infrared sensors from satellite imagery. Long dry season with a low rainfall rate was suspected as the main cause of many fire alerts in the lower part of peatland. We retrieved and processed rainfall data from Tropical Rainfall Measuring Mission (TRMM) as an input to calculate the dryness classification using Standardized Precipitation Index (SPI), as well as fire alerts data from VIIRS (Visible Infrared Imaging Radiometer Suite) satellite imagery during 2015 - 2019. This research aims to analyze the relationship between the dryness peatland condition and the intensity of fire alerts by generating a correlation graph between drought on a long dry season and fire alerts generated from VIIRS. Forest fires are very susceptible to occur at the SPI drought index showing a number <-1 with the classification "quite dry,"

Keywords: TRMM Rainfall Data, SPI, Hotspot, Forest fire, Mitigation.

1. INTRODUCTION

Based on the Central Bureau of Statistics of Indonesia in 2020, the Kalimantan region in Borneo Island has 36.5 million ha of tropical forest area or 30,2% of state forest area. More importantly, around 30,951 km² or 20% of the area of Central Kalimantan is peatland (Hooijer et al. 2006). Unfortunately, many fires happen nowadays in peatlands. Peatland is a land unit that consists of piles of organic matter mixed with branches and wood roots with a depth of between 2 and 10 meters, black, cannot hold water (is porous), and flammable (Pasaribu and Friyanto. 2006). In 1996, the Indonesian government initiated the Mega Rice Project (MRP) to develop a million hectares of rice fields in the tropical swamp-forest between the Sebangau and Barito rivers in Central Kalimantan, Indonesia. More than 63% (9,191 km²) of the total MRP area is peatland, converted to other land uses (Notohadiprawiro 1998). The MRP ended in 1999, but the project has left vast drained peatland areas and brought severe peat fire problems as a result. Peat fires in this area become very active mainly during droughts or El Niño years' dry season. However, many fires were also occurring in the dry season of non-El Niño years when the Niño 3.4 SST anomaly had small positive values, as occurred in 2001, 2003, and 2005 (Putra et al. 2008).

The forest and land fires that occurred in 2015 and 2019 in Central Kalimantan were the worst in Kalimantan island in terms of the area of land burned (BBC News). According to the Indonesian Ministry of Environment and Forestry data, around 22,35% (583.833 ha) of burned forest areas in Indonesia during 2015 forest fire cases happened in Central Kalimantan. While in the 2019 Indonesian forest fires, around 19,26% (317.749 ha) of burned forest areas also happened in Central Kalimantan. According to the Indonesian National Board for Disaster Management and Ministry of Environmental and Forestry data, the land burned area in Central Kalimantan from 1 July - 20 October 2015 is 196.987 ha. Throughout 2019, the burned land area is up to 183.836 ha affecting wildlife, human health, the region's economy, and local and global climate.

Peat fire is influenced by several factors, i.e., peat and weather characteristics, peat water content, peat decomposition rate, water level, and rainfall. According to Syaufina et al. (2004), the higher the water content in peat, the lower the burning rate. According to Harrison et al. (2009), fires are a product of climatic conditions and anthropogenic factors. In Indonesia, tropical fires occur on Indonesian peatlands and peat-swamp forest (PSF) in the dry season and, unsurprisingly, are worse in drier years. The Indonesian climate is strongly influenced by the El Niño Southern Oscillation (ENSO): in El Niño years, dry-season rainfall can be less than half of regular and severe El Niño events have long been associated with fire (e.g., 1972-73, 1982-83, 1987, 1991-92, 1994, 1997-98, 2002, 2006). Thus, peatland drainage is the principal cause of the recent increased frequency and severity of tropical peatland fires. Besides, land fires are also caused by anthropogenic factors, that is when peatlands over dried because of the dry season and less of rainfall deliberately prevented from getting wet again so they can be converted into plantations. In contrast, dry peatlands can return to being wet by rainfall and other water sources.

The primary purpose of this research is to prove the relationship between the level of dryness of peatland and fire alerts number using VIIRS satellite imagery. The level of dryness of peatland is obtained from rainfall TRMM data. The dryness of peatland is negatively correlated with rainfall. The lower the amount of rainfall, the drier the land will be. Rainfall data will be analyzed using SPI methods to classify the dryness level. The Indonesian government has an interest in preventing forest and land fires. However, efforts are needed to diagnose both natural and artificial factors that trigger fires and risk management strategies to reduce drought vulnerability.

2. DATA PREPARATION

2.1 VIIRS Fire Alerts Data

The data used in this research include remote sensing data and meteorological data. This study's remote sensing data are Visible Infrared Imaging Radiometer Suite (VIIRS) fire alerts product. We acquired VIIRS fire products from the Global Forest Watch website. The databases in the global forest watch are grouped into specific regions. This allows the data to be downloaded only in the Central Kalimantan region. The data was already collected in the form of a comma-separated file (CSV) to convert this data into analytical graphs. We calculate the mean average fire alerts within a month between 2015 and 2019. Because peatlands often generate a heat source beneath the surface, the fire alerts data is a suitable source for determining the fire susceptibility. The data we selected was daily data, but there are several days without data. This happens because there are no hotspots to generate in the selected region. The data was calculated into average monthly fire alerts in order to match meteorological data.

2.2 TRMM Rainfall Data

The second data source we used in this research is the Tropical Rainfall Measuring Mission (TRMM) to generate average rainfall during specific periods. Based on the average fire alerts and meteorological data, we can determine the potential forest fires during a particular time. TRMM data are available to be downloaded from NASA Geospatial Interactive Online Visualization ANd aNalysis Infrastructure (Giovanni) open data portal. NASA Giovanni Open Data Portal is a system that provides access to a wide variety of NASA remote sensing data and other Earth science data sets, allowing researchers to apply selected data to a broad range of research topics such as this research (Acker et al., 2014). The data we selected is subsetted to the boundaries of Central Kalimantan Province.

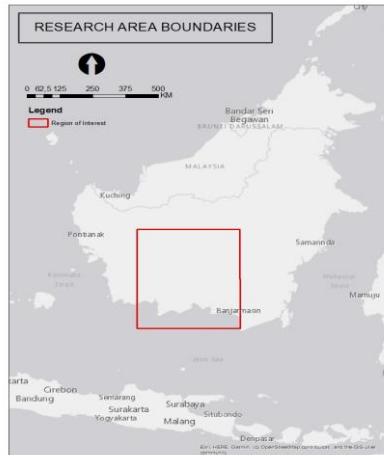


Figure 1. Selected area boundaries

We constructed the time series precipitation plots based on the type of selected dataset on the Giovanni platform. The available datasets include rainfall data, precipitation in various forms, the water content in clouds, and soil moisture data to reach a refresh rate every 3 hours up to a month resolution. The data available starts from 25 km up to 0.5 degree (around 55 km) depending on the selected data type in terms of spatial resolution. This research's rainfall data are daily rainfall data acquired from TRMM 3B42 satellite from 2015 to 2019. Daily rainfall is selected in order to match fire alerts data also generated in daily data. The selected area boundaries are within the coordinate range of the Central Kalimantan region with a resolution of 0.25 degrees. We download the data in the form of a sheet table and generate area-averaged, time series plots to get a quick data overview. The plot format represents the average rainfall amount based on the selected rainfall dataset and within the selected boundaries.

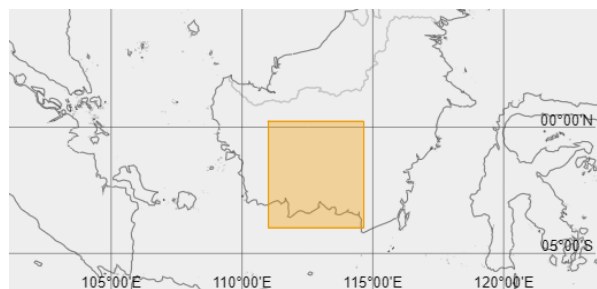


Figure 2. selection process (NASA Giovanni)

3. METHODS

Drought conditions in the region trigger the causes of forest fires. This drought becomes a severe problem if it occurs over a considerable period. The initial period occurring from droughts is generally undetermined, but drought can be indicated when there is a lack of water needed for a region's living creatures. From a disaster perspective, drought is defined as a lack of rainfall in a certain period (generally in one season or more) that causes a shortage of water for various needs (UN-ISDR, 2009). Drought is generally classified as meteorological, hydrological, agricultural, and socio-economic (Soentoro 2015). Meteorological drought is a drought measured by a constant lack of rainfall. Hydrological drought is a drought because of a

shortage of surface water and groundwater supply. Agricultural drought is a drought because of the water content on land that does not meet individual plants' needs in a particular period. A socio-economic drought is a reduction in demand due to a drought affecting the region's economic condition.

Dryness can be classified into several categories depending on the type of parameter used where the index can be used to identify the drought condition. There are various kinds of indexes that can be used in determining drought, for example, Percent of Normal (PN), Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), Crop Moisture Index (CMI), Surface Water Supply Index (SWSI), Reclamation Drought Index (RDI), Deciles and TLM (Indarto, Wahyuningsih, Pudjojono, Ahmad, & Yusron, 2014). The drought index is created depending on the region of research, users, processes, inputs, and outputs, and until now, there is no universally applicable hydrological drought index (Hatmoko, 2012). In this study, the Standardized Precipitation Index (SPI) was used. The SPI model was chosen because it has the advantage of being reliable, having a flexible and straightforward index in the calculation (McKee et al., 1993). In the SPI method, the parameter index used is the monthly rainfall parameter. This method analyzes the monthly rainfall for an extended period. The index classification level of SPI, according McKee (1993), was presented on table 1 and the calculation can be found on the Equation 1.

Table 1. Classification SPI Index

SPI Values	Classification
>2,00	Extreme wet
1,50 – 1,99	Very wet
1,00 – 1,49	Moderately wet
0,99 – 0,00	Normal
0,00 – (-0,99)	Near normal
-1,00 – (-1,49)	Moderately dry
-1,50 – (-1,99)	Very dry
< -2,00	Extremely dry

Source: (Mckee et al. 1993)

$$\text{Classification of SPI in Month} = \frac{X_{ij} - X_{im}}{\sigma} \dots \dots \dots (\text{Eq.1})$$

Information

X_{ij} = actual rainmonth (i) (year) at one rainfall station (j) on time of observation.,
 X_{im} = average rainfall (i) on a specific time scale., σ = standard deviation

Source: (Mustaqim & Priyana , 2016)

The classification of SPI index serves as an essential reference in the analysis to state the conditions of the relationship between fire alerts and rainfall to get a provide preventive and curative mitigation analysis of forest fire disasters.

4. RESULTS AND DISCUSSION

4.1 Fire Hotspots during 2015-2019 periods

High fire alerts count usually happens during the dry season in Indonesia between early July and last till early November. The fire alerts count shown in the table below indicates the 2015 hotspot was reaching its highest count with an average of 598 fire alerts during a single year. The same phenomena were almost repeated during 2019 years but still only reached the least number with 254 fire hotspots spotted. Based on the table below, we can conclude that the highest count always happens between September and October during the peak dry season.

Table 2. Average Fire Alerts Count

Periods	Average	Periods	Average	Periods	Average	Periods	Average	Periods	Average
Dec-15	13	Dec-16	3	Dec-17	3	Dec-18	1	Dec-19	7
Nov-15	134	Nov-16	13	Nov-17	3	Nov-18	4	Nov-19	262
Oct-15	2741	Oct-16	45	Oct-17	34	Oct-18	100	Oct-19	228
Sep-15	2642	Sep-16	40	Sep-17	39	Sep-18	270	Sep-19	2106
Aug-15	927	Aug-16	29	Aug-17	4	Aug-18	162	Aug-19	345
Jul-15	91	Jul-16	4	Jul-17	7	Jul-18	28	Jul-19	75
Jun-15	16	Jun-16	4	Jun-17	5	Jun-18	8	Jun-19	6
May-15	7	May-16	4	May-17	3	May-18	5	May-19	4
Apr-15	3	Apr-16	2	Apr-17	2	Apr-18	2	Apr-19	2
Mar-15	3	Mar-16	3	Mar-17	2	Mar-18	3	Mar-19	4
Feb-15	5	Feb-16	3	Feb-17	6	Feb-18	11	Feb-19	3
Jan-15	5	Jan-16	4	Jan-17	2	Jan-18	6	Jan-19	3
mean	598	mean	13	mean	9	mean	50	mean	254

While analyzing the fire alerts graph, we found a sharp incline during the 2015 and 2019 periods, especially in the dry season periods. In 2015 and 2019, there was a long dry period because of low rainfall rate due to strong El Nino. Meanwhile, from 2016 to 2018, the wet period was relatively high, with the number of fire alerts observed quite low. Although there are several fires alerts inclination during the 2018 dry season but not significant compared to those 2015 and 2019.

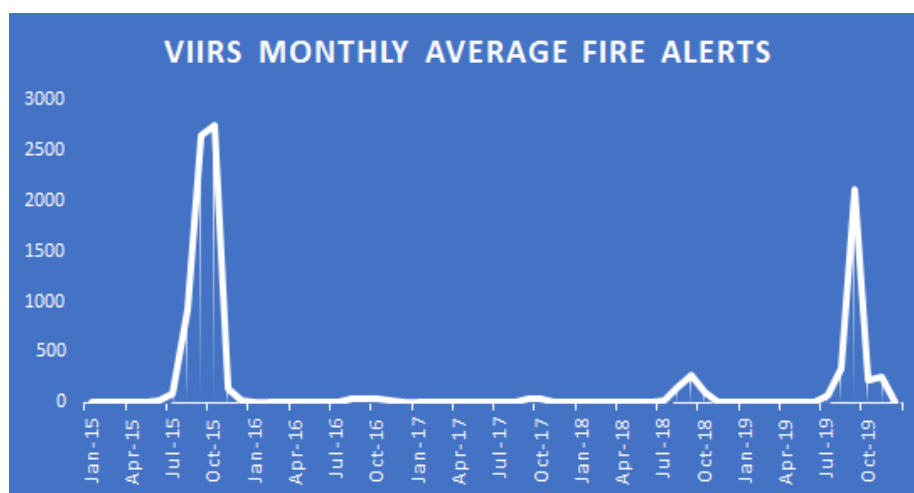


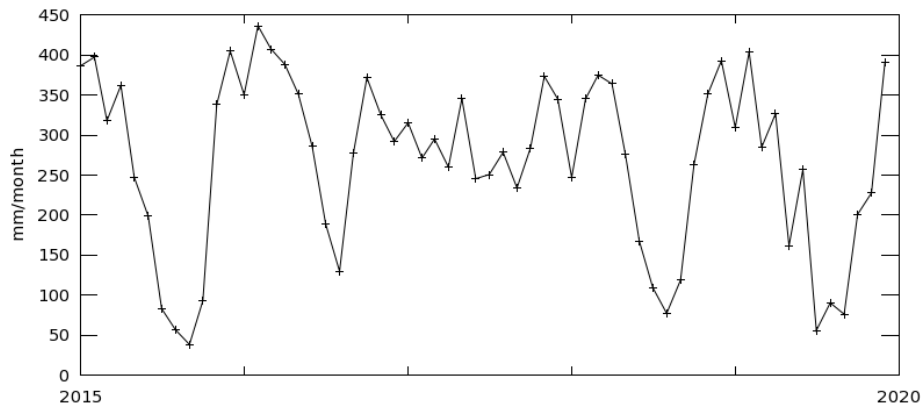
Figure 3. Average Fire Alerts Graph

4.2 Rainfall during 2015-2019 periods

Based on the selected are boundaries, we create a plotted time series rainfall graph, as shown in figure 2. According to the graph, the rainfall rate between early time series data and

twice near the end data is reaching low rates at almost below 50 mm/month. In the same time period, the fire alerts are increasing, as shown in figure 2.3 There are several low rainfall events in the next periods but never reach their lowest points.

Time Series, Area-Averaged of Precipitation Rate monthly 0.25 deg. [TRMM TRMM_3B43 v7] mm/month over 2015-Jan - 2019-Dec, Region 111.0084E, 3.9887S, 114.6559E, 0.23N



- The user-selected region was defined by 111.0084E, 3.9887S, 114.6559E, 0.23N. The data grid also limits the analyzable region to the following bounding points: 111.125E, 3.875S, 114.625E, 0.125N. This analyzable region indicates the spatial limits of the subsetted granules that went into making this visualization result.

Figure 4. Rainfall Rate Plot

The rainfall data is also downloaded as table data, as shown in Table 3 below. There are identified some low-rate rainfall during specific periods—the lowest rainfall rate achieved in the 2015's dry season, especially in September and October. The rainfall rate achieved 38 and 93 mm/month, respectively. At the same time, fire alerts reached its highest count with 2642 and 2741 fire alerts spotted, respectively. However, almost every period in the following years experience the same phenomena but never reaching the same number as the 2015 years. The second-highest number as of 2019 occurred during the 2019 seasons.

month	Rainfall (mm/month)	SPI Index	Classification	month	Rainfall (mm/month)	SPI Index	Classification
Jan-15	386	1,09	Moderately wet	Jul-17	251	-0,16	Near Normal
Feb-15	397	1,19	Moderately wet	Aug-17	278	0,09	Normal
Mar-15	318	0,46	Normal	Sep-17	234	-0,32	Near Normal
Apr-15	362	0,87	Normal	Oct-17	284	0,14	Normal
May-15	247	-0,20	Near Normal	Nov-17	373	0,97	Normal
Jun-15	199	-0,64	Near Normal	Dec-17	345	0,71	Normal
Jul-15	83	-1,71	very dry	Jan-18	247	-0,20	Near Normal
Aug-15	57	-1,96	very dry	Feb-18	345	0,71	Normal
Sep-15	38	-2,12	Extremely dry	Mar-18	375	0,98	Normal
Oct-15	93	-1,62	very dry	Apr-18	364	0,88	Normal
Nov-15	338	0,65	Normal	May-18	275	0,07	Normal
Dec-15	405	1,26	Moderately wet	Jun-18	168	-0,93	Near Normal
Jan-16	350	0,76	Normal	Jul-18	109	-1,47	Moderately dry
Feb-16	436	1,55	Very wet	Aug-18	77	-1,76	very dry
Mar-16	408	1,29	Moderately wet	Sep-18	119	-1,38	Moderately dry
Apr-16	388	1,11	Moderately wet	Oct-18	263	-0,05	Near Normal
May-16	351	0,77	Normal	Nov-18	351	0,77	Normal
Jun-16	286	0,16	Normal	Dec-18	393	1,15	Moderately wet
Jul-16	189	-0,73	Near Normal	Jan-19	310	0,38	Normal
Aug-16	130	-1,28	Moderately dry	Feb-19	404	1,25	Moderately wet
Sep-16	277	0,08	Normal	Mar-19	285	0,15	Normal
Oct-16	372	0,95	Normal	Apr-19	327	0,54	Normal
Nov-16	325	0,53	Normal	May-19	162	-0,98	Near Normal
Dec-16	292	0,22	Normal	Jun-19	257	-0,11	Near Normal
Jan-17	315	0,43	Normal	Jul-19	56	-1,96	very dry
Feb-17	271	0,03	Normal	Aug-19	91	-1,64	very dry
Mar-17	295	0,25	Normal	Sep-19	76	-1,77	very dry
Apr-17	260	-0,08	Near Normal	Oct-19	201	-0,62	Near Normal
May-17	345	0,71	Normal	Nov-19	228	-0,38	Near Normal
Jun-17	246	-0,21	Near Normal	Dec-19	391	1,13	Moderately wet

Table 3. Rainfall data and SPI Classification

4.3 SPI Value Classification

Monthly rainfall data were processed into categories of wet months or dry months using the SPI index method. This classification aims to determine the level of drought conditions in months. The positive values indicate that the classified month shows wet conditions, and the negative values indicate that the month analyzed shows dry conditions. Based on the SPI results, the lowest drought value index was obtained in September 2015 with a value of -2.12 with the extremely dry classification category. The second-lowest value in the next periods achieved in July 2019 with a value of -1.96 with the very dry classification category.

4.4 Correlation Between SPI and fire alerts

The SPI method's transformed data are correlated with the number of fire alerts that occurred in the same period in the correlation graph. Based on the graph shown below, there is a negative relationship between the two data. When SPI represents rainfall, it shows a negative value. It means the lands are getting drier because of a very low rainfall rate. At the same time, fire alerts count shows a very significant increase. This fact shows that if the peatlands worsen because of the low rainfall rate, the heat source beneath the lands is increasing. This phenomenon often leads to forest fires if some other factors increase forest fires. The trends also show that if SPI value cannot reach at least dry classification, the increase in fire alerts was not significant. This happens during the 2016 and 2017 dry seasons. Fire alerts count rose again in the 2018 dry season when SPI reached a very dry (1.5) value. However, the increase in fire alerts was not too significant compared to 2015 and 2019 when the SPI value reached very dry (> 2.00), causing the number of fire alerts to increase very sharply.

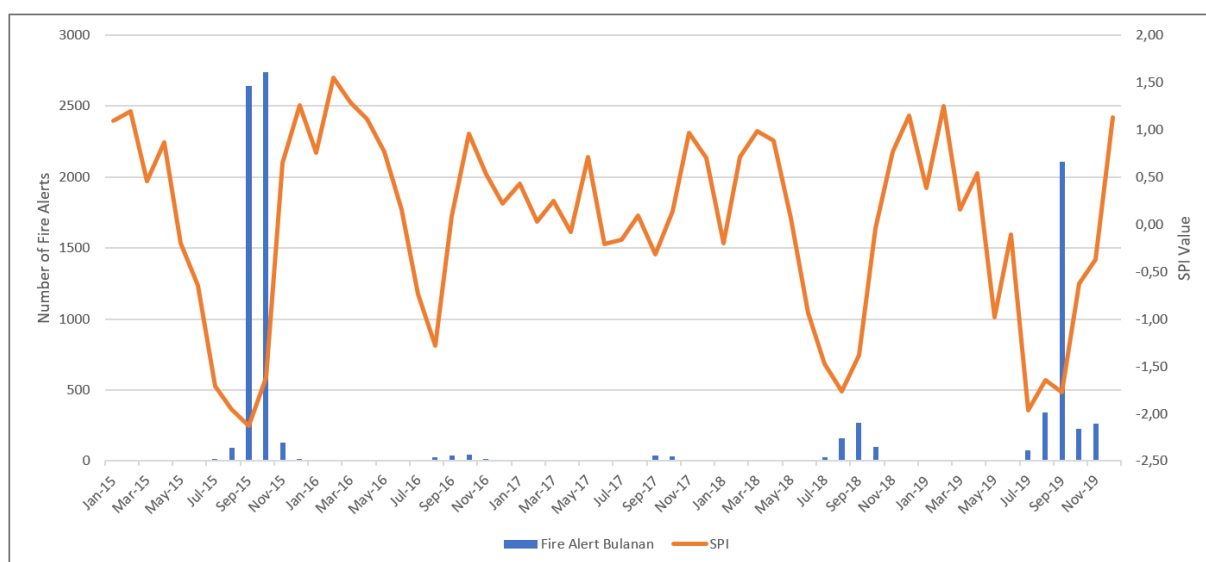


Figure 5. SPI and Fire Alerts Correlation Graph

The high count of fire alerts also correlates with the amount of burned forest in Central Kalimantan. The highest Fire Alerts recorded in 2015 also coincided with the broad area of

burned forest. Recorded in that year, the area of forest burnt in Central Kalimantan reached 583,833 hectares. While in 2019, when the fire alerts increased again, the area of forest burned was relatively high, reaching 317,749 hectares. Based on the fact, it should be made early warnings against climatological phenomena that occur, such as when the rainfall rate decreases hugely. Artificial watering such as water-bombing, may be the closest alternative to dealing with hotspots that are spotted under the peatlands. Disaster management that can be carried out by a forest fire is to continue to carry out water bombing. However, what is necessary here is that water bombing must still be done with the same amount of rainfall in the rainy season when rainfall can reduce hotspot fires. The SPI's safe limit is at a value of -1 (supposedly normal) or approximately 200mm / month of rainfall based on SPI and Fire Alerts correlation graphs.

5. CONCLUSION

In this study, vulnerability analysis of forest fire disasters in peatland areas was carried out. The data parameters used were hotspot data and rainfall data, which were processed by the SPI drought index method. From the correlation analysis results between the rainfall data processed by the SPI method and fire alert data, the results of the negative correlation between the two variables were obtained. This shows a decrease in the fire alert graph with an increase in the amount of rainfall. This analysis produces two main outputs in forest fire disaster mitigation. Forest fires are very susceptible to occur at the SPI drought index showing a number <-1 with the classification "quite dry," therefore for preventive mitigation of forest fires. Water bombing must be carried out so that the SPI index does not fall below the number -1 or the conditions are relatively dry when a forest fire occurs. A curative (healing) effort that can be done is by doing water bombing again by making monthly minimum rainfall in the range of 200mm / month so that the index SPI returns to a number above -1. This makes disaster mitigation more efficient and targeted.

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