Analyzing Rainfall and Greenness Vegetation Level on Forest/Land Fire Area in Jambi and Central Kalimantan Provinces using Remote Sensing Data

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Abstract. El-Nino, which occurred in 2019 in Indonesia, caused longer dry conditions than usual. Low rainfall and vegetation drought cause widespread forest/land fires. This study aims to know the relationship between drought conditions and forest/land fires from the parameters of rainfall and vegetation greenness level. The study located in Jambi and Central Kalimantan Provinces during the peak months of fires which is September 2019. To see fluctuations in the peak of fires, eight daily data were taken for this period. Extraction of rainfall information is derived from the Himawari-8 infrared band L1 image into L2 rainfall rate data. Vegetation greenness level information is derived from Terra / Aqua MODIS red and near-infrared band images into L2 Enhance Vegetation Index (EVI) data. Hotspot data comes from the images of Terra, Aqua MODIS, SNPP VIIRS, and NOAA20. Fire data was extracted from hotspot data and delineation of MODIS RGB image smoke. Rainfall fluctuation affects the number of forest/land fire hotspots. The decrease in rainfall was followed by an increase of hotspot numbers and vice versa. In Jambi Province, rainfall decreased in first to second period i.e. 40 to 0 mm was followed by an increase of hotspot number which dominated by high confidence level. In Central Kalimantan rainfall increased from third to fourth period i.e. 0 to 100-400 mm followed by the decreasing of hotspot number which dominated by medium confidence level. Meanwhile, the TKV variable had little effect on the number of hotspots but related with rainfall data. In Central Kalimantan Province, the driest TKV (0.1) on September 14-21, 2019, was influenced by low rainfall in the previous period which also has highest number of fire hotspots. In Jambi Province, the driest TKV happened on third period which also the result of lowest rainfall and highest number of fire hotspot in the previous period.

Keywords: hotspot, fire haze, Terra/Aqua MODIS, confidence level.

1. Introduction
Drought conditions that generally occur during the dry season are often used to burn forests/land by some irresponsible people. This condition often results in the spread of forest/land fires in Indonesia, especially in Sumatra and Kalimantan. Although in recent years, forest/land fires have also occurred in Papua, Sulawesi, and Nusa Tenggara Timur. The impacts of the forest/land fires not only disrupt human activities, damage ecosystems, destroy some flora and fauna, but also cause quite high economic losses.
In 2019, based on World Bank calculations quoted by the Head of Centre for Data and Information, National Disnaster Management Agency in Kompas online news, the economic loss due to forest/land fires was around 75 trillion Rupiah with a total burned area of around 942,484 hectares [1]. This loss value is higher than the conditions in 2018 and 2017 because 2019 coincides with the El Nino phenomenon which makes the intensity of forest/land fires very high. Therefore, considering its very detrimental impact, monitoring and evaluating of forest/land fire incidents are still very relevant to be studied and analysed as a mitigation effort.

There is a very close relationship between drought conditions and forest/land fires. Fires are more easily ignited and spread more widely in conditions of drought and low rainfall. In very dry conditions, especially during the El Nino episode where the period of low rainfall lasts longer, the chances of fire occurring will be higher, as well as its spread [2]. Based on the results of the review by Littell et al. on historical data on forest fire incidents in North America, the area and incidence of forest fires tended to increase in response to drought [3]. In addition, Littell et al. also stated that the interaction between drought and other controllers, such as: forest productivity, topography, fire weather, and management activities, also affect the intensity, level of vulnerability, extent, and frequency of fires. Thus, monitoring drought conditions as an early step and anticipating forest/land fires is very necessary. Analysis of the relationship between drought and the incidence of forest/land fires still needs to be studied, so that efforts to predict and early warning forest/land fires can be carried out earlier.

According to Sukmawati, climate and weather factors that can affect forest/land fires are humidity, air temperature, rainfall, and wind [4]. Air humidity affects water content of the fuel and the incidence of fire, while the temperature of the air in the drought area, especially in the dry season, rainfall on the humidity and water content of the fuel, and wind on the acceleration of fuel drying and the spread of fire when a fire occurs. Based on the research results of Adiningsih et al. found that rainfall and Normalized Difference Vegetation Index (NDVI) are geophysical factors that have a major contribution to the incidence of forest/land fires compared to the land cover type [5]. Based on Syaufina et al., although not directly, rainfall correlates with the occurrence of forest/land fires [6]. In Indonesia, forest/land fires are generally caused by human activity. However, the condition of reduced and decreased rainfall triggers human behaviour to burn. Therefore, monitoring of rainfall conditions every month is very necessary to predict and early warning against fire hazards.

LAPAN has used 2 (two) parameters in monitoring drought, which are Greenness Vegetation Level (TKV) which is derived from the MODIS Enhanced Vegetation Index (EVI) data and, monitoring of rainfall accumulation from the Himawari-8 data. Drought monitoring using the TKV parameter is intended to monitor vegetation conditions. Meanwhile, the accumulated rainfall from Himawari-8 monitors rainfall conditions for specific periods (10 minutes, 12 hours, daily, eight days, months, and years). There is a very close relationship between rainfall patterns and changes in greenness vegetation level [7, 8]. Al Bakri and Suleiman [7] analysed the relationship between the NDVI values derived from NOAA / AVHRR from 1981 - 1992 with station rainfall from 16 weather stations in 4 (four) ecological zones in Jordan. Meanwhile, Gunnula et al.[8] examined the relationship between NDVI derived from MODIS data and rainfall patterns in the Northeastern region of Thailand. The decrease in accumulated rainfall in the dry season will have a further impact on decreasing the greenness vegetation level due to reduced soil moisture or drought. In forest vegetation, drought will have an impact on increasing the risk of forest fires [9]. According to Li et al. [10], changes in the EVI value are closely related to the severity of the fire. The higher the change in the EVI value after a fire, the more severe the fire will be. This condition will be exacerbated by the ongoing season.

Meanwhile, monitoring of forest/land fires by LAPAN is carried out using hotspot data. The hotspot data is extracted from Terra / Aqua MODIS data, SNPP VIIRS, and NOAA-20. The research aims to determine the condition of TKV and accumulated rainfall at the location of forest/land fires in the provinces of Jambi and Central Kalimantan during the fire period in 2019.
2. Materials and Method

2.1. Location and Data

The research location took the Sumatra and Kalimantan regions represented by Jambi and Central Kalimantan Provinces. The two provinces have the highest number of hotspots in Indonesia in 2019, especially in September. Figure 1 below shows the research locations and the number of hotspots in the peak month.

![Figure 1](image)

**Figure 1.** Hotspot (a) September in Central Kalimantan (b) October in Central Kalimantan (c) September in Jambi (d) October in Jambi

The data used in this study are L2 Enhanced Vegetation Index (EVI) imagery from Terra / Aqua MODIS and L2 rainfall rate data derived from Himawari-8 data. Terra / Aqua MODIS data has a spatial resolution of 250 m, 500 m, and 1000 m and has 36 bands that work in the spectral range 620 - 14,385 nm [11]. The EVI index is derived from the red and near infrared bands with a spatial resolution of 1 km x 1 km. Meanwhile, the Himawari-8 imagery used is Himawari cast with a spatial resolution of 4 km x 4 km. The L2 rainfall rate data is derived from the infrared band at a spectral 11,000 nm.

Hotspot data is used as an indicator of forest/land fires which can be extracted from Terra / Aqua MODIS, SNPP VIIRS, and NOAA20 imagery. Hotspot data has latitude and longitude coordinate information, which is the centre point of the image pixel. Hence, an indication of forest/land fires is within a radius of 1 km according to the image resolution. Apart from the hotspot data, a visual interpretation of smoke from Terra / Aqua MODIS imagery is also used. The smoke hotspot locations indicate the certainty of forest/land fires.

In this study, the data used were the accumulated data of eight days of rainfall, eight daily TKV, and the accumulated number of hotspots eight days. The determination of the 8-day accumulation of each type of data used in this study is based on the Julian date during the forest/land fire period in both regions. Table 1 describes in detail the data used in this study.
Table 1. Details of the types of data used in the study.

| L1 Data            | L2 Data          | Time                                      |
|--------------------|------------------|-------------------------------------------|
| Terra/Aqua MODIS   | EVI              | 1. 29 August – 5 September 2019            |
| Himawari 8         | Rainfall rate    | 2. 6 – 13 September 2019                  |
| Hotspot (Terra/Aqua MODIS, NOAA20, SNPP VIIRS) | 3. 14 – 21 September 2019               |
|                    |                  | 4. 22 – 29 September 2019                 |
|                    |                  | 5. 30 September – 7 October 2019          |
|                    |                  | 6. 8 – 15 October 2019                    |
|                    |                  | 7. 16 – 23 October 2019                   |
|                    |                  | 8. 24 – 31 October 2019                   |

2.2. Method

a. Pre-processing (geometric and radiometric correction)

Image correction is a process of image conditioning so that it is precisely radiometric and geometric [12]. Geometric correction improves geometric quality so that the coordinates in the image match the location in the field. Radiometric correction has function to improve the spectral image. In this study, geometric and radiometric corrections were carried out systematically for Himawari-8 and Terra/Aqua MODIS images. This correction improves the image position. Then, the process of clipping or cutting images at the study locations in Jambi and Central Kalimantan Provinces.

Radiometric correction is carried out systematically by the system to improve the digital image value. Terra/Aqua MODIS imagery records the accumulative value of the object's reflection for eight days. The Himawari-8 image records the reflection of the cloud object for an estimated CH value every 10 minutes, which is then accumulated for eight days of recording.

b. EVI and rainfall extraction

Enhanced Vegetation Index (EVI) is a vegetation index designed to identify canopy structures [13–15]. Based on Liu and Huete [13], extraction of the EVI value is derived from the following formula 1:

\[ EVI = G \times \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + (C_1 \times \rho_{red} - C_2 \times \rho_{blue}) + L} \] (1)

Where L is the soil adjustment factor = 1. C1 and C2 are the coefficients to improve the aerosol scattering = 6 and 7.5. G is a coefficient of 2.5. \( \rho_{nir} \) and \( \rho_{red} \) are the reflectances of near infrared and red band of Terra/Aqua MODIS imagery.

Rainfall extraction is based on infrared band-1 on the Himawari-8 image [16]. The band is converted into a rainfall rate image which has units of rainfall in mm per pixel.

c. Classification of Greenness Vegetation Level (TKV) and Rainfall

The vegetation index value describes the condition of Greenness Vegetation Level (TKV) [17]. The value of the vegetation index used in this study is the EVI index with a value range of 0 - 1 where the value of 1 shows the optimal value of the index or the optimal value of vegetation and vice versa. There are six classification classes in Indonesia, namely cloud/water, very low, low, medium, high, and very high [18]. Very low indicates dry vegetation conditions; this is associated with poor vegetation drought conditions. Vice versa, for the very high TKV class, it indicates optimal vegetation conditions so that it does not indicate vegetation dryness. Table 2 below shows the division of TKV classes.

Table 2. Classification of Greenness Vegetation Level
Meanwhile, rainfall per pixel/8 day is classified into five classes, namely very low, low, medium, high, and very high. Rainfall conditions relate to the meteorological drought conditions of a region. The lower the rainfall indicates the drought conditions of an area and vice versa. Table 3 below shows the division of rainfall classes used in this study.

| Rainfall class | Rainfall accumulation value (mm) |
|---------------|----------------------------------|
| Very low      | 0 – 50                           |
| Low           | 50 – 100                         |
| Moderate      | 100 – 300                        |
| High          | 300 – 500                        |
| Very high     | >500                             |

**Table 3.** Classification of rainfall

d. Hotspot overlay
Hotspot data has information i.e. confidence level, latitude and longitude coordinates and, administrative location. The level of confidence in hotspots is divided into three i.e. high, medium, and low confidence classes [18]. These three classes are correlated with fire incidence. The higher the level of confidence, the higher the probability of fire, and vice versa. The hotspot data is then overlaid on TKV and rainfall images for the Jambi Province and Central Kalimantan Province.

e. TKV and rainfall extraction in hotspot location
At the coordinates of the fire hotspot, the TKV and rainfall values were extracted using the extract values to point technique. The TKV and rainfall values are values for one pixel that overlaps the hotspot so that each TKV value represents an area of 1 km square and the rainfall value represents an area of 4 km squares.

f. Spatial and temporal analysis of TKV and rainfall in forest/land fire locations.
The fire distribution map is displayed over the image of TKV and rainfall in September 2019 for the eight days period. The distribution of hotspots and the level of confidence were analysed in the location of their distribution. To find out the TKV and rainfall values at the fire location, the comparison chart of the TKV values and hotspot of low, medium, and high-level were used, as well as the CH values. The following Figure 2 shows the research flow diagram.
3. Result and Discussion
Rainfall in Central Kalimantan is dominated by very low class (0-50mm) in 3 periods: 29 August - September 2019, 6-13 September 2019, and 14-21 September 2019. In the fourth period, 22-30 September 2019, rainfall conditions begin to rise in the range of 50-200 mm. In the first period, there were 5072 hotspots of all categories. If it is seen from Figure 3, the number of medium-confidence hotspots is the largest among others and is followed by the high-security hotspots category. Likewise, for other periods, the order of the highest number of hotspots is in the medium, high, and low categories. The low category has a small number and a significant comparison with the medium and high categories. This condition shows that the location of the fire which was accompanied by smoke in Central Kalimantan, was dominated by medium and high confidence level hotspots. The highest number of hotspots was on September 6-13, 2019 with the number of medium hotspots 4902, high hotspots 4057, and low hotspots 508. During this period, the monthly rainfall was in very low conditions, namely 0-25 mm. There was a pattern of decreasing number of hotspots in the fourth period (22-30 September), namely 3021 medium hotspots, 2269 high hotspots, and 325 low hotspots, this was also followed by an increase in rainfall to 0-400 mm in the high, medium, low, and high rainfall categories.

![Figure 2. Research flow diagram](image)

Figure 2. Research flow diagram

![Figure 3. Rainfall chart of Central Kalimantan](image)

Figure 3. Rainfall chart of Central Kalimantan
Figure 4. Rainfall map of Central Kalimantan

Figure 5 shows a graph of rainfall in Jambi Province where the highest number of hotspots was in the lowest rainfall, namely September 6-13, 2019. On that date, almost all hotspots were in areas without rain (0 mm) with a high number of hotspots of high confidence, namely 1625 and medium hotspots 1233. In contrast to the province of Central Kalimantan, Jambi province in September 2019 was dominated by very low-class rainfall. There was no increase in rainfall in the fourth period. Another difference with Central Kalimantan, the highest number of hotspots in Jambi Province on all dates is high-confidence hotspots followed by medium-confidence hotspots and low-confidence hotspots.

Figure 5. Rainfall chart of Jambi

Figure 6. Rainfall map of Jambi
TKV, which is one of drought parameters, is indicated by dry vegetation conditions when experiencing water shortages for a certain period. The TKV map of Central Kalimantan in Figure 8 shows the distribution of TKV dry classes that widened in the third period. This condition happened because there was a decrease in rainfall in the previous two periods. TKV started to improve in the fourth period. The distribution of hotspots does not fully follow the pattern of dry TKV, several areas with dry TKV and an increase in the number of hotspots, namely Kab. Gunung Mas, Katingan and Kotawaringin Timur.

In the third period, where the distribution of dry TKV is the widest, the number of hotspots is still high, but not the highest, namely in the third period. This condition shows that the driest conditions for TKV do not affect the number of hotspots but are the result of fires in several districts. The driest TKV occurred in the fourth period after the peak of the fires in the third period.

**Figure 7. TKV charts of Central Kalimantan**

**Figure 8. TKV maps of Central Kalimantan**
4. Conclusion

The drought conditions seen from the rainfall and TKV affect the incidence of forest/land fires. Rainfall fluctuation affects forest/land fire hotspot number. A decrease in rainfall is followed by an increase in the number of hotspots and conversely an increase in rainfall affects a decrease in hotspot number. In Jambi Province, rainfall decreased in first (Agst 29-Sept 5, 2019) to second period (September 6-13, 2019) i.e. 40 to 0 mm was followed by an increase of hotspot number. In Central Kalimantan rainfall increased from third (Sept 14-21, 2019) to fourth period (Sept 22-30, 2019) i.e. 0 to 100-400 mm followed by the decreasing of hotspot number. Meanwhile, the TKV variable had little effect on the number of hotspots but related with rainfall data. In Central Kalimantan Province, the driest TKV (0.1) on September 14-21, 2019, was influenced by low rainfall in the previous period which also has highest number of fire hotspots. In Jambi Province, the driest TKV happened on third period which also the result of lowest rainfall and highest number of fire hotspot in the previous period. The difference between two province is the dominating hotspot confidence level. Central Kalimantan Province is dominated by high level while Jambi Province is dominated by medium level.
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