ESTIMATION OF FOREST FIRE AREAS IN PALANGKA RAYA, CENTRAL KALIMANTAN, INDONESIA USING NBR2 AND ITS IMPACT ON ENVIRONMENT

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ESTIMATION OF FOREST FIRE AREAS IN PALANGKA RAYA, CENTRAL KALIMANTAN, INDONESIA USING NBR2 AND ITS IMPACT ON ENVIRONMENT. Indonesia, particularly Palangka Raya City in Central Kalimantan, boasts approximately 241,736.25 hectares of forested areas crucial for human survival. Despite their significance, these areas are plagued by annual forest fires that lead to damage and adverse effects on the environment, including vegetation health and air quality. This research sought to pinpoint the extent of forest fire occurrences and their repercussions by analyzing changes in vegetation health and air quality through remote sensing technology. The study employed various remote sensing techniques, such as the Normalized Burn Ratio 2 (NBR2) for detecting burned areas, the Enhanced Vegetation Index (EVI) for assessing vegetation health, and $PM_{2.5}$ for analyzing air quality. Utilizing Landsat-8 satellite imagery data as the primary source, the research successfully identified burned areas with an impressive overall accuracy of 82.229% using the NBR2 index. The findings revealed a direct correlation between forest fires and increased air pollution, particularly in $PM_{2.5}$ levels, as well as a decline in vegetation health in the vicinity of the burned areas. These results highlight the importance of continuous monitoring of forest fire occurrences and their impact through remote sensing data to mitigate their adverse effects.

Keywords: Air quality, burned area, remote sensing, spectral indices, vegetation health

ESTIMASI LUAS KEBAKARAN HUTAN DI KOTA PALANGKA RAYA, KALIMANTAN TENGAH, INDONESIA MENGGUNAKAN NBR2 DAN DAMPAKNYA TERHADAP LINGKUNGAN. Indonesia khususnya Kota Palangka Raya yang terletak di Kalimantan Tengah memiliki kawasan hutan dengan luas sekitar 241.736,25 hektar. Kawasan hutan tersebut mempunyai peranan penting bagi kelangsungan hidup manusia. Namun setiap tahunnya, kebakaran hutan selalu terjadi dan menimbulkan kerusakan hutan, berdampak pada kondisi lingkungan seperti kesehatan vegetasi dan kualitas udara. Penelitian ini bertujuan untuk mengidentifikasi kawasan kebakaran hutan dan dampaknya berdasarkan kesehatan vegetasi dan perubahan kualitas udara dengan menggunakan teknologi penginderaan jauh. Metode penginderaan jauh yang digunakan dalam makalah ini adalah indeks spektral kebakaran Normalized Burn Ratio 2 (NBR2) untuk identifikasi area terbakar, Enhanced Vegetation Index (EVI) untuk mengidentifikasi kesehatan vegetasi, dan $PM_{2.5}$ *untuk analisis kualitas udara. Data citra satelit Landsat-8 digunakan sebagai data primer untuk mengekstraksi area terbakar dan dampaknya. Area terbakar yang dihasilkan NBR2 menunjukkan akurasi keseluruhan yang tinggi yaitu 82,229%. Studi tersebut menunjukkan bahwa kebakaran hutan berdampak pada polusi udara dengan peningkatan besar dalam paparan* $PM_{2.5}$ *setelah kebakaran hutan, dan penurunan kesehatan vegetasi, yang terjadi di sekitar area yang diidentifikasi sebagai area yang terbakar. Dengan hasil tersebut, identifikasi kawasan kebakaran hutan dan dampaknya dapat dipantau secara terus menerus menggunakan data penginderaan jauh guna meminimalkan dampak kebakaran hutan.*

Kata kunci: Area terbakar, indeks spektral, kesehatan vegetasi, kualitas udara, penginderaan jauh

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I. INTRODUCTION

Climate change has been a critical topic in recent years with Sustainable Development Goals (SDGs) serving as one of the solution to tackle climate change (Nurfindarti et al., 2019). The forest is utterly important to help achieve SDGs since it hosts various ecosystems and is able to provide various natural resources for human well-being (Baumgartner, 2019). Palangka Raya City has extensive peat swamp forest (Page et al., 2011). The forest area of Palangka Raya reaches up to 84.73% of the entire 285,312 hectares of the city area (BPS, 2021). Given the size of this tropical rainforest, it is imperative that the natural resources found there be preserved. The 2019 forest fire was identified as the largest forest fire accident from 2017 to 2020 based on shapefile data of forest fire released by the Center for Climate Change and Forest and Land Fires Control for the Kalimantan Region in 2021.

The forest floor is covered by a highly combustible organic layer, a consequence of human activities like the construction of drainage canals. These canals have led to reduced water tables, gradually drying out the surface peat layers and making them susceptible to fires. The presence of this highly flammable organic layer, combined with the traditional farming practices in Kalimantan involving controlled burning for land clearance, has resulted in numerous forest fire incidents (Goldstein et al., 2020). Forest fires could cause various problems including air pollution (Chen et al., 2021) and a decrease in vegetation health (Pérez-Cabello et al., 2021). Forest fires have the potential to cause soil to become more water-resistant, causing runoff which has an impact on increasing soil erosion rates (Datta, 2021). Higher temperatures cause dry peatland to burn, leaving the topsoil bare and reducing the capability for new plants to grow (Martin et al., 2016).

Identification of the burned area and its impact can be carried out through various methods. One of which is using remote sensing technology. Remote sensing can be used in risk estimation, detection and assessment of fire management (Sunar & Özkan, 2001). Remote sensing data uses surface vegetative structure and spectral features to give precise, quick, and trustworthy information for post-fire impact studies. (Somashekar et al., 2009). The identification of forest fires by remote sensing has been widely employed, utilizing fire spectral indexes such as the Burned Area Index (Chuvieco et al., 2002). Previous research conducted by Sukojo and Aini (2018) in Bromo Mountain, East Java, and Pujana (2020) and Cahyono et al. (2021) in Palangka Raya used the Normalized Burn Ratio (NBR) and Normalized Difference Vegetation Index (NDVI) algorithms to identify burnt areas and the severity of the fire. It is rare to come across research that analyses burnt area points and their impact on the dynamics of air pollution and vegetation health.

Another study, Lutes et al. (2006) developed an NBR algorithm to become Normalized Burn Ratio 2 (NBR2) in order to identify burn areas in the United States. NBR2 is a modified model from NBR that highlights water sensitivity in vegetation (Lutes et al., 2006). It is hoped that NBR2 can lessen identification errors brought on by water, as it is one source of inaccuracy for burned area identification. Because NBR2 performs well at identifying burned areas, it can conduct post-fire recovery studies (Hislop et al., 2018). NBR2 outperformed other burned area indices such as NBR, MSI, EVI, and GRND in burned area identification (De Souza et al., 2021). In all previous studies, there was a threshold model which was used to distinguish the burned and unburned areas. The threshold also determined the accuracy of the burned area identification model. The thresholds used were μ -1σ, μ, and μ+1σ.

The impact of forest fires on vegetation in Palangka Raya City can be identified by the Enhanced Vegetation Index (EVI) because EVI is developed for areas with a high level of vegetation density (Huete et al., 2002), thus it is suitable to be applied in Palangka Raya because Palangka Raya is mostly covered with forest area based on BPS Data (2021)s. EVI is also capable of detecting short-term and long-term vegetation changes (Berlanga-Robles & Ruiz-Luna, 2020). Since it can reduce atmospheric and soil background noise at the same time, it is more sensitive to topographic conditions than the conventional NDVI (Huang et al., 2019).

The amount of $PM_{2.5}$ present in the burned area indicates how forest fires affect the quality of the air. $PM_{2.5}$ is a mixture of particulates having a size equal to or less than $_{2.5}$ microns. Excessive $PM_{2.5}$ exposure is harmful to human health (World Bank, 2020). $PM_{2.5}$ identification can be conducted by observing the band on remote sensing data which has a good correlation with air quality parameters. Somvanshi's method identified $PM_{2.5}$ by detecting three bands that have the closest correlation with the $PM_{2.5}$ data based on the linear regression of all Landsat-8 bands on $PM_{2.5}$ data (Somvanshi et al., 2019). Through multiple linear regression, a mathematical model will be obtained for the identification of $PM_{2.5}$ exposure in the burned area (Somvanshi et al., 2019). Somvanshi's method is based on a mathematical model that is adaptable for any location across the earth if there is relevant $PM_{2.5}$ data (Somvanshi et al., 2019).

In previous researches, remote sensing data were used, such as MODIS (Sukojo & Aini, 2018), Landsat-8, and VIIRS (Pujana, 2020; Saputra et al., 2017). As for field data, hotspots of burnt areas were used (Pujana, 2020; Saputra et al., 2017). Compared to MODIS and VIIRS, Landsat-8 has a higher spatial resolution. Therefore, using data from Landsat 8 satellite imagery, this research focuses on locating the Palangka Raya burned region in 2019 and observing its effects on vegetation health and air quality based on $PM_{2.5}$. Analysis was also done on how well the NBR2 algorithm identified Palangka Raya City's burned regions. The purpose of this study was to give a more realistic picture of how forest fires affect both vegetation and people. The results are expected to help prevent forest fire catastrophes in the future.

II. MATERIAL AND METHOD

A. Study Site and Materials

This research was part of the 2022 ITS (Institut Teknologi Sepuluh Nopember) Scientific Research Project, which looked into the Palangka Raya City, Central Kalimantan, Indonesia, forest fire incident that occurred in 2019. This research identified burn areas located in Palangka Raya City. Palangka Raya's geographic coordinates are as follows: 113°30'–114°04' East Longitude and 1°30'–2°30' South Latitude, as shown in Figure 1. The Landsat-8 surface reflectance tier 1 satellite image data for the time frame prior to and following the forest fire occurrence were used in this investigation.

The National Agency for Disaster Countermeasures's historical data on land and forest fires in 2019 shows that a number of fire occurrences were reported between May 5 and July 27, 2019. Therefore, the pre-occurrence range of forest and land fires (pre-fire) was taken from August 2018 to May 2019, and for events after forest and land fires (post-fire) were taken from August 2019 to December 2019. Based on data from the Central Kalimantan Province Forest Fire Task Force command post, it was noted that the largest fire incident occurred in Palangka Raya City on 14 September 2019 with a burned area of 1,955 hectares. Validation data was derived from the burned area reported by the Indonesian Center for Climate Change and Forest and Land Fires Control (Balai PPI and Karhutla).

B. Methods and Analysis

Identification of burned areas was done using Normalized Burn Ratio 2 as a burned area index, following Equation 1 (Lutes et al., 2006):

$$NBR2 = \frac{\rho SWIR1 - \rho SWIR2}{\rho SWIR1 + \rho SWIR2},$$

Where $\rho SWIR1$ is the......................(1) reflectance of Shortwave Infrared 1 Band and $\rho SWIR2$ is the spectral reflectance of Shortwave Infrared 2 Band. The threshold of the burned area models was then

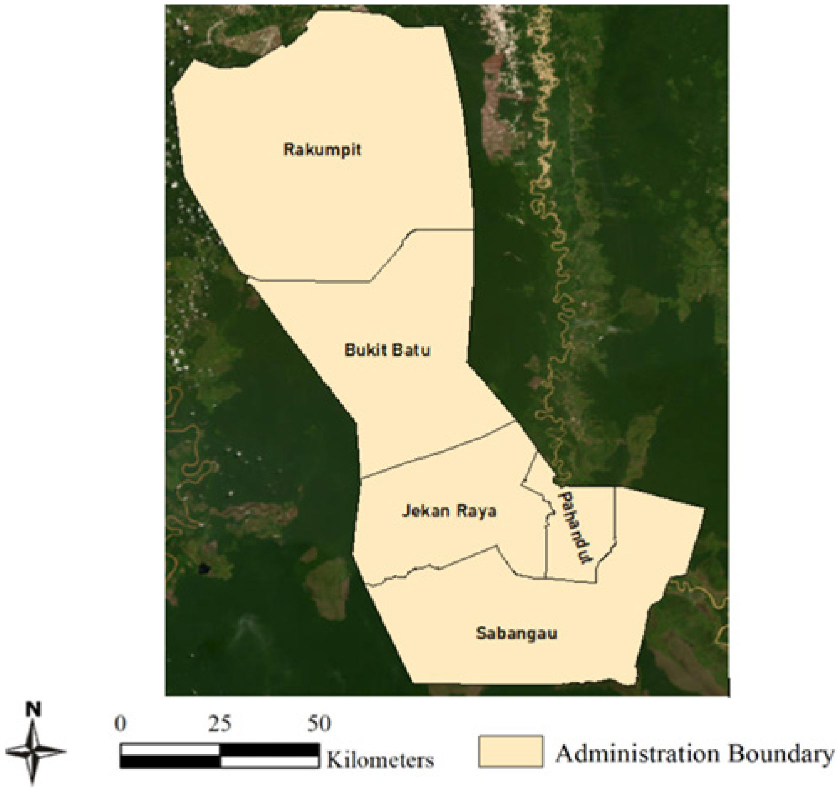


Figure 1. Map of Palangka Raya

established following the completion of the burned area identification procedure. The value known as the threshold is used to differentiate between burned and unburned areas. Three threshold models exist: μ-1σ, μ, and μ+1σ. The average and standard deviation of the index are denoted by μ and σ respectively. Thresholding was carried out when the burned area was identified. (Chuvieco et al., 2002).

Identification of vegetation health was conducted using the Enhanced Vegetation Index (EVI), a spectral index developed by minimizing the influence of atmospheric disturbances and optimizing vegetation signals with increased sensitivity in areas of high vegetation density (Huete et al, 2002). EVI is ideal for areas with high canopy or high vegetation density. EVI was calculated by using Equation 2 (Huete et al., 2002) as follows:

$$EVI = G\,\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + l} \quad \text{............(2)}$$

Where G is the gain factor that is represented with the value of $_{2.5}$, ρ_{NIR} is the reflectance of the near-infrared band, ρ_{red} is the reflectance of the red band, ρ_{blue} is the reflectance of the blue band, $C_1$is the aerosol coefficient 1 represented by the value of 6, C_2 is the aerosol coefficient 2 represented by the value of 7.5, and l is the adjusting value for the canopy background represented by the value of 1 (Huete et al., 2002). Furthermore, EVI values can also be used to identify vegetation health, such as an EVI value of -1 until 0 is classified as dead plants, an EVI value of 0 until 0.33 is classified as unhealthy plants, an EVI value of 0.33 until 0.66 is classified as moderately healthy plant, and an EVI value of 0.66 until 1 is classified as very healthy plants (EOS, 2019).

Identification of $PM_{2.5}$ exposure was done using Somvanshi's method, which used different Landsat-8 bands that showed good correlation with air quality parameters based on a linear regression between Landsat-8 band and air quality parameters. $PM_{2.5}$ was the only air quality parameter analyzed in this research. The equation for identification of $PM_{2.5}$ exposure is as follows (Somvanshi et al., 2019):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad \text{....................(3)}$$

Where Y is $PM_{2.5}$; β_0, β_1, β_2, and β_3 are the coefficients. X_1, X_2, and X_3 are the maximum correlated bands. Based on Equation 3 a linear regression needs to be performed to find out which bands have the best correlation with $PM_{2.5}$. This process resulted in a new $PM_{2.5}$ identification equation for post-forest fire as follows:

$$Y = \beta_0 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 \quad \text{....................(4)}$$

Equation 4 was formed based on band 5, band 6, and band 7 which had a good correlation with $PM_{2.5}$ post-fire compared to other bands. Another equation can be formulated from equation 3 for pre-fire $PM_{2.5}$ identification. The equation was formed based on band 1, band 2, and band 3 which had a good correlation with $PM_{2.5}$ pre-fire compared to other bands.

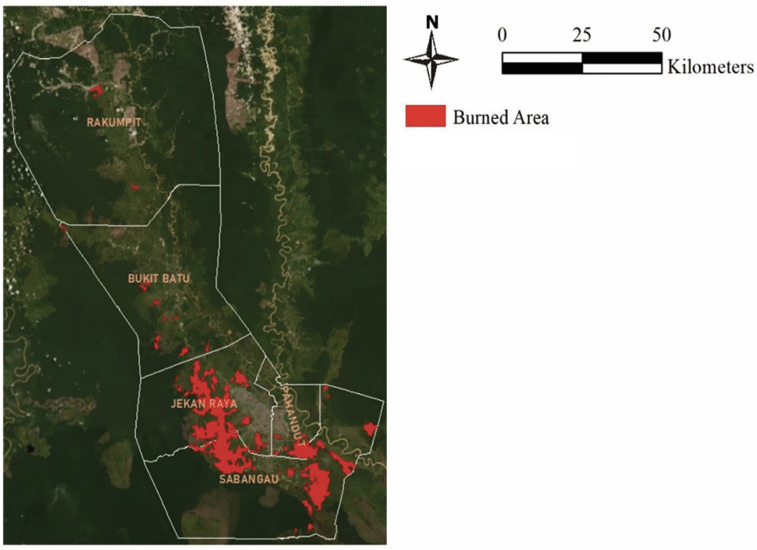
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \, , \quad \text{..................(5)}$$

Validation data was obtained from the Kalimantan Region of Indonesia's Center for Climate Change and Forest and Land Fires Control (Balai PPI and Karhutla). Confusion matrix accuracy assessment was used to carry out the burned areas validation process. The confusion matrix is often used to evaluate and validate remote sensing data. Using the validation data as its ground truth, the confusion matrix is used to validate the threshold model. (Gholamrezaie et al., 2022). In the confusion matrix, overall accuracy can be used as the parameter for accuracy assessment. The weighted average of a test's specificity and sensitivity, where specificity is weighted by the complement of prevalence and sensitivity is weighted by prevalence, is called overall accuracy.

III. RESULT AND DISCUSSION

A. Identification of Burned Area

Three different threshold types were used by Normalized Burn Ratio 2 (NBR2), yielding three different burned area models. To determine which threshold provides the best identification, validation is required. The validation data indicates that 16,292.514 hectares of Palangka Raya were burned in 2019. Figure 2 displays the validation data's burned areas.. The most accurate threshold model was employed for further analysis.



Source: Center for Climate Change and Forest and Land Fires Control (Balai PPI and Karhutla) Kalimantan Region, Indonesia, 2019

Figure 2. Burned area validation data based on 2019 fire incident

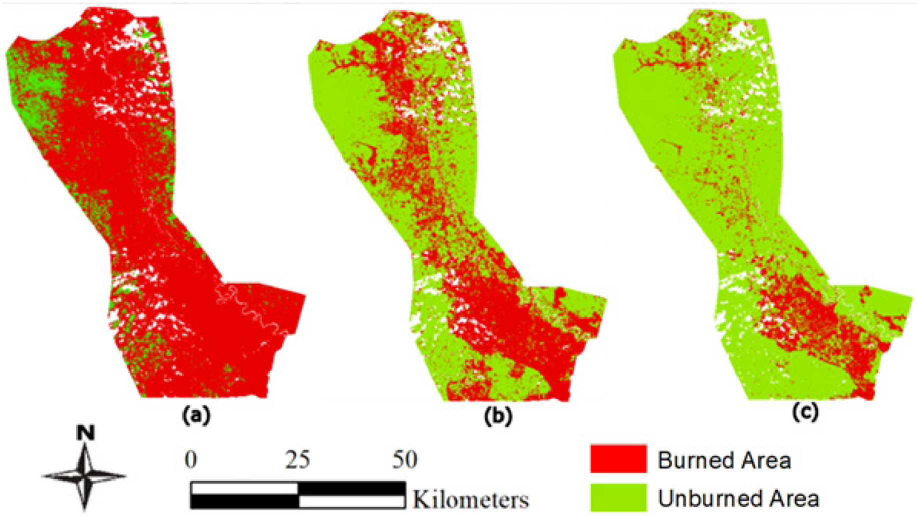


Figure 3. Burned Area from NBR2 with threshold model: (a) – μ+1σ; (b) – μ; (c) – μ-1σ

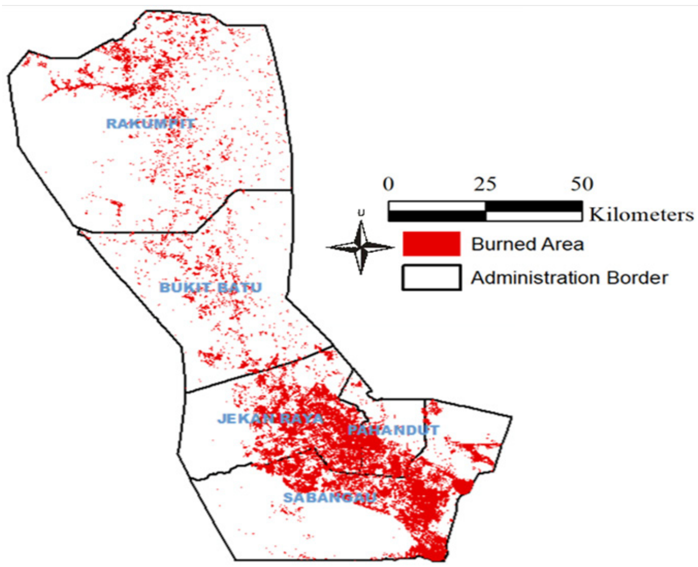


Figure 4. μ - 1σ Burned area model

NBR2 threshold models and accuracy reports are shown in Figure 3 and Table 1. Based on the accuracy report, the μ + 1σ threshold showed the worst performance in identifying burned areas with an accuracy of 17.282%, and the μ - 1σ threshold achieved the best performance in identifying burned areas with an accuracy of 82.229%. In order to facilitate further analysis, the burned area with the threshold μ - 1σ was chosen. Based on how they are distributed throughout Palangka Raya City's subdistricts, the distribution of areas burned in 2019 can be examined. Pahandut, Sabangau, and Jekan Raya Sub-Districts contained the majority of the burned areas (Figure 4).

Table 1. Accuracy assessment of NBR2 threshold models for burned area detection.

Threshold	Overall Accuracy
μ + 1σ	17.3%
μ	65.6%
μ - 1σ	82.2%

Table 2. Distribution of burned areas in Palangka Raya (May 2019 – July 2019) based on the NBR2 Identification

Subdistrict	Burned Areas (hectare)
Pahandut	3,720.288
Sabangau	15,216.090
Jekan Raya	12,469.832
Bukit Batu	4,453.222
Rakumpit	8,507.354
Total	**44,366.784**

Based on Table 2, Sabangau District was the sub-district with the largest burned area with 15,216,090 hectares and the least burned area was observed in Pahandut with 3,720.288 hectares. The three most populous districts in Palangka Raya are Pahandut, Sabangau, and Jekan Raya districts. Controlled burning by traditional farmers was suspected to be the cause of forest and land fires. Land clearing method that is not strictly controlled or supervised might lead to large forest fires. The concentration of forest fires in the sub-districts of Sabangau, Pahandut, and Jekan Raya supports the theory that there is a direct relationship between population density and burned areas in Palangka Raya. The Palangka Raya burned areas were well-represented in the NBR2 model, which had an accuracy of 82.2%. Due to the sensitivity of NBR2 to the presence of water in vegetation, over-detection occurred, with the presence of water being one of the weaknesses of various fire detection algorithms. This over detection had a specific pattern that resembled burned forests or land areas.

NBR2 outperforms some algorithms in detecting forest fires based on satellite imagery. Saputra et al. (2017) noted an accuracy of 70.97% by using NBR and Landsat-8 satellite imagery. Sukojo and Ainun's study (2018) that used NDVI had 48.394% accuracy on Landsat-8 and 57.089% on MODIS satellite. Meanwhile, Pujana (2020) showed 82.15% overall accuracy by using NDVI and 85.85% by using NBR in Landsat-8 imagery. In this recent research, the NBR2 result showed a better burned area identification than most of the previously mentioned studies. Therefore, NBR2 exceeds both NBR and NDVI burn area detection in similar location environment profiles.

B. Identification of Vegetation Health

The spatial distribution of vegetation health was obtained by using the Enhanced Vegetation Index (EVI). Vegetation health is divided into four classes, namely dead plants, unhealthy plants, moderately healthy plants, and very healthy plants (EOS, 2019). Figure 5 shows a significant increase in areas of unhealthy plant classes post-fire incident by 45.581% or 4,779.353 hectares, suggesting a compromised vegetation health in the identified burned areas.

Several points of vegetation health decline can be seen through the distribution of the unhealthy plants class which shows an expanding

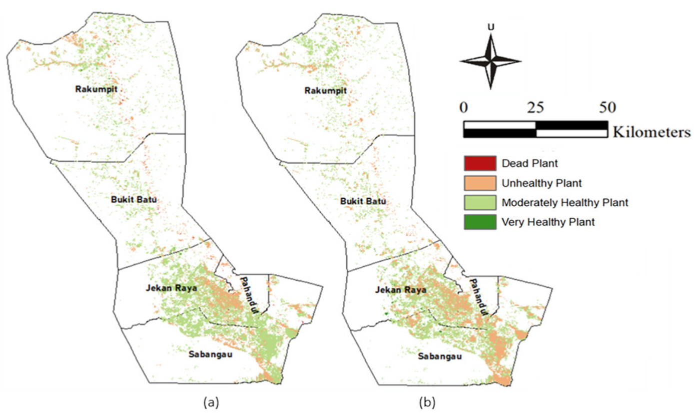


Figure 5. Vegetation Health in Palangka Raya: (a) pre-fire; (b) post-fire

area, especially in forest areas surrounding urban areas. This is in accordance with validation data which stated that forest fires occur around urban areas. The structure of the Palangka Raya forest, which is a peat swamp forest, is disrupted by agricultural activities which create dry peat layers on the surface of the forest floor that are highly flammable because draining peatlands eliminates the natural fire protection that intact peatlands provide. However, a slight increase in the class of healthy vegetation can be seen in areas far from residential areas, presumably due to the distance from human settlements thus lack of anthropogenic activities were done in this area.

C. Identification of $PM_{2.5}$ Exposure

The spatial distribution of $PM_{2.5}$ exposure was obtained using the Somvanshi $PM_{2.5}$ identification method. The result is shown in Fig 6. The average $PM_{2.5}$ exposure in Palangka Raya after the 2019 forest fire event was 56.140μg/m^3. The average exposure of $PM_{2.5}$ in Palangka Raya before the 2019 forest fire was 24.854μg/m^3. There is a significant change in average exposure of $PM_{2.5}$ between pre- and post-fire that shows the great impact of fire incident on $PM_{2.5}$ exposure in Palangka Raya. This led to an increase in air pollution because of the smoke produced by forest fires.

Air Pollutant Standard Index based on Minister of Environment and Forestry Regulation No. 14 of 2020 can be calculated assuming that the average value of $PM_{2.5}$ exposure is the $PM_{2.5}$ exposure in 24 hours. Therefore, in this study, post-fire $PM_{2.5}$ exposure is equal to 100.9278 or 101 in the Air Pollutant Standard Index score which is categorized into not healthy class. The $PM_{2.5}$ Exposure in Palangka Raya post the 2019 forest fire was harmful to humans, animals, and plants.

NBR2 and $PM_{2.5}$ had a high correlation with a value of 0.730 in the linear regression analysis. The scale of the correlation coefficient was based on research from Hair et al (2006). The $PM_{2.5}$ identification is representative of real-world conditions at the time after the forest fire event. $PM_{2.5}$ changes between post- and pre-fire showed a significant increase in the area located near the centre of the city, while there are some reductions around the urban area but close to the forest area (Figure 6). Therefore, besides forest fires, human activity seemingly also contributed to the rise of $PM_{2.5}$ exposure post-fire.

D. Sample Point Analysis

The 2019 fires in Palangka Raya city were concentrated in Jekan Raya, Pahandut, and Sabangau districts. Therefore, a focused analysis was then conducted in those areas in order to see a more detailed impact of the fire on the changes in $PM_{2.5}$ exposure and vegetation health. Sample points distribution is shown in Figure 7. The sample points were collected inside the boundary of NBR2 burned area with the selected threshold model. The sample points were used to analyze the changes in $PM_{2.5}$ value between pre- and post-fire in the burned areas. Table 3 shows those changes from each sample point.

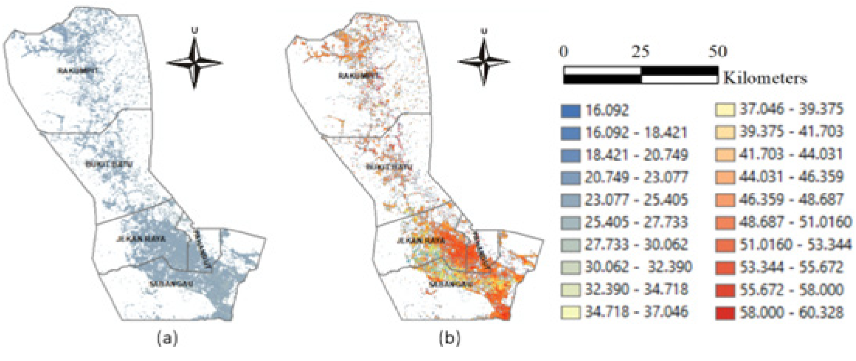


Figure 6. PM2.5 Exposure in Burned Areas: a – pre-fire; b – post-fire

Table 3. Vegetation health value changes between pre- and post-fire

Label	NBR2	Vegetation Health			$PM_{2.5}$ (μg/m^3)		
		Pre-fire	Post-fire	Differences	Pre-fire	Post-fire	Differences
A	0.124	0.383	0.171	-0.213	25.179	55.418	30.239
B	0.145	0.541	0.301	-0.240	25.028	55.246	30.218
C	0.203	0.454	0.238	-0.216	25.188	56.725	31.537
D	0.224	0.249	0.292	0.044	25.029	56.316	31.287
E	0.193	0.510	0.267	-0.243	24.944	56.017	31.073
F	0.067	0.534	0.125	-0.409	24.826	54.257	29.431
G	0.090	0.545	0.176	-0.368	25.228	55.18	29.952
H	0.214	0.414	0.288	-0.126	25.295	57.01	31.715
I	0.145	0.494	0.247	-0.247	25.191	55.413	30.222
J	0.164	0.511	0.242	-0.270	25.519	56.364	30.845
K	0.168	0.42	0.232	-0.188	25.106	56.152	31.046
L	0.175	0.523	0.248	-0.274	25.438	54.235	28.797
M	0.199	0.520	0.252	-0.268	25.289	56.493	31.204
N	0.243	0.311	0.278	-0.033	24.991	56.553	31.562
O	0.205	0.193	0.26	0.067	25.555	56.207	30.652
P	0.176	0.563	0.160	-0.403	25.251	55.671	30.42
Q	0.256	0.507	0.267	-0.240	25.55	57.217	31.667
R	0.175	0.457	0.301	-0.155	25.37	56.49	31.12

Point F showed the highest changes in vegetation health between pre- and post-fire with a value of -0.409. The location of point F was quite far from the city, and mostly forested area. The significant decline in vegetation health in point F is assumedly due to slash and burn land clearing done by some traditional farmers around the area that consequently affected the vegetation health there. Meanwhile, point K showed a moderate change in vegetation health between pre and post-fire, which was -0.188 (Table 3). As shown in Figure 7, point K was located considerably far from the centre of the city. Differences between point K and point F can be seen in Fig 7 which point K showed a darker profile than point F. While point F was located far from roads, point K was near a sand road, where human activities can be detected. This meant that the vegetation in point K already had a lower vegetation health than in point F before the forest fire. Point D showed the lowest changes in vegetation health (+0.044). This point was located near a river and possibly is an intact peat swamp forest considering its location. Therefore, the fire outbreak did not significantly impact point D due to its intact swamp forest condition.

Point H showed the highest $PM_{2.5}$ exposure difference between pre- and post-fire with a value of +31.715 μg/m^3. The significant increase in $PM_{2.5}$ was presumably due to its proximity to the city, whereas local farmers might have done slash-and-burn land clearing practices and the street traffic intensity of the city. Point L showed the lowest changes in $PM_{2.5}$ exposure (28.797 μg/m^3). This point was located far from the centre of the city. As shown in Fig 7, point L might be a dense forest because of the color differences compared to points K and H, which meant that point L has limited accessibility to humans and vehicles. Hence, resulted in less forest fire and less impact on $PM_{2.5}$ exposure.

NBR2 is proven to be a good burn area index because it produces 82.2% overall accuracy. outperforming most of the previous study burn area model (Pujana. 2020; Saputra

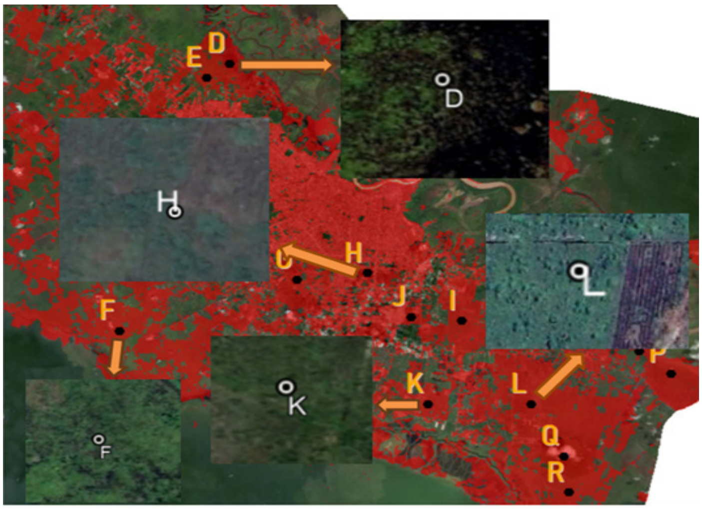


Figure 7. Sample point used to analyze the locations of fire incidents

et al., 2017; Sukojo & Aini, 2018). While previous studies on burn area identification did not analyze the correlation between burn area and its impact, this current study addresses the forest fire impact on vegetation health and air quality. This study highlights the impact, not only in the form of a hypothesis but also proven by the vegetation health and $PM_{2.5}$ identification. Therefore, this study is able to give a broader range of analysis regarding forest fire's impact on the environment and human health. Accordingly, the findings could advise a suitable recommendation for the decision makers to design a better disaster prevention and mitigation plan.

The authors should compare the findings of their study with previous studies, especially on discussion about the impact of forest fires on human health and environmental conditions, which could be studied with different methods or different locations or even different parameters.

IV. CONCLUSION

NBR2 with μ - 1σ model produced a 44,366.784 hectare burned area with an overall accuracy of 82.2%. NBR2 outperforms some burn area indices in previous studies with the same environment profile. Forest fire impacted vegetation health as shown by a total area of 17,704.259 hectares for the dead plants class and the unhealthy plants class. There was also an increase in area by 45.581% for the unhealthy plants class. This result showed that the 2019 forest fire had a huge impact on the degradation of vegetation health. $PM_{2.5}$ identification showed that air quality in Palangka Raya city after the 2019 forest fire was classified as not healthy class based on the Regulation of the Minister of Environment and Forestry No. 14 in 2020. $PM_{2.5}$ exposure was found to be higher at all sample points near the city compared to sample points that are far away from the city. This indicates the involvement of human activities in forest fire incidents that negatively affect human health and air quality.

It is recommended to design a forest fire mitigation and prevention plan, especially for Jekan Raya, Pahandut, and Sabangau sub-districts as these areas are most affected by forest fires. Future research can be developed to make a better burn area algorithm that suits the Kalimantan environment profile using image fusion and other remote sensing techniques

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