Jurnal Belantara Vol. 8, No.2, August (235-244)
DOI: 10.29303/jbl.v8i2.1143
E-ISSN 2614-3453
P-ISSN 2614-7238

FOREST FIRE DETECTION BASED ON GOOGLE EARTH ENGINE SEBANGAU NATIONAL PARK

Afifah Kiki Dwi Wulandari [1]**, Beni Iskandar** [1*]**, Sari Marlina** [1]

[1] Forestry Study Program, Faculty of Agriculture and Forestry, Universitas Muhammadiyah Palangkaraya

* Email: beniiskandar@umpr.ac.id

Received: 15/06/2025, Revised: 05/08/2025, Approved: 08/08/2025

ABSTRACT

Sebangau National Park, a peatland conservation area, is particularly vulnerable to forest fires. These conflagrations are most prevalent during the dry season. The objective of this research is to detect and analyze burned areas in Sebangau National Park using the Google Earth Engine (GEE) platform. The analysis will utilize Landsat 8 satellite imagery from 2015. The methods employed for detecting areas that have undergone combustion include the utilization of Normalized Burn Ratio (NBR) and Normalized Difference Vegetation Index (NDVI) indices. The analysis reveals that the burned area, as determined by the NBR index, encompasses 27,567.92 hectares. When assessed using NDVI, the burned area increases to 35,163.44 hectares. The accuracy assessment reveals that the NDVI index exhibits an Overall Accuracy (OA) value of 97.71% and Kappa Accuracy (KA) of 81.46%, which exceeds the NBR by 0.07% and 1.24%, respectively. This finding highlights the enhanced precision of NDVI in detecting vegetation changes resulting from fire events. Consequently, NDVI can serve as a crucial reference point in post-fire mitigation and rehabilitation efforts within peat conservation areas.

Keywords: Forest fire; Google earth engine; NDVI; NBR; Sebangau national park

INTRODUCTION

Sebangau National Park is one of the national parks located in Central Kalimantan Province. According to the Decree of the Minister of Forestry No. 423/Menhut-II/2004 dated October 19, 2004, Sebangau National Park has been designated as a peatland conservation area and wetland reserve, with the objective of preserving the area's biodiversity, including the Bornean Orangutan and Gibbon, which represent the park's most prominent wildlife. Estimate the total population of orangutans in Sebangau National Park to be approximately 6,900 individuals (Morrogh-Bernard et al., 2003). However, there are periodic threats of damage, including the possibility of forest fires. In 2015, Sebangau National Park suffered significant forest fires, leading to damage estimated at approximately 4,364 hectares and economic losses amounting to IDR 134 billion (Khalwani et al., 2015).

The utilization of remote sensing technology in the endeavor to promote the sustainable management of Sebangau National Park has the potential to facilitate the acquisition of crucial information, particularly about the identification of areas that have been affected by fire (Rahmia et al., 2020). Conventional remote sensing approaches generally entail the download and processing of images on geographic information system software to detect burnt areas. This process is particularly time-consuming in the context of image analysis, particularly when attempting to analyze extensive regions (Zurqani et al., 2019).

In view of the rapid advancements witnessed in the domain of computational capabilities in recent years, there is an increasing demand for sophisticated computational tools to support remote sensing investigations and analysis (Ma et al., 2015). Google Earth Engine (GEE) is a computing platform with millions of servers around the world and the latest cloud computing capabilities. GEE facilitates remote sensing analysis by archiving extensive catalogs of Earth observation (EO) data and leveraging the vast repositories of satellite images stored in Cloud Computing (Dong et al., 2016). GEE facilitates remote sensing analysis by archiving extensive catalogs of Earth observation (EO) data and leveraging the vast repositories of satellite images stored in Cloud Computing (Farhadi et al., 2022).

Sebangau National Park is characterized by a peat ecosystem, which renders it highly vulnerable to fire. The use of Google Earth Engine (GEE) is essential in mapping burned areas quickly and efficiently. The identification of areas that have been affected by fire is imperative for the estimation of the magnitude of destruction, the evaluation of ecological consequences, and the formulation of recovery strategies and the generation of data-driven reports. Furthermore, the utilization of GEE in the mapping of burned areas is of paramount importance in the context of long-term monitoring and evaluation of the efficacy of restoration policies. This approach facilitates the analysis of recurrent fire trends and the identification of spatial patterns that were previously challenging to discern. The objective of this study is to utilize GEE to analyze the burned area within Sebangau National Park.

METHOD

Research Location

The research location was located in Sebangau National Park, Central Kalimantan Province, with a geographical location of 2°35′0″ north latitude and 113°40′0″ east longitude (Figure 1). Sebangau National Park is in the regency of Katingan (52%), Pulang Pisau (38%), and Palangka Raya City (10%). The research was conducted over a period of six months, from November 2024 to April 2025.

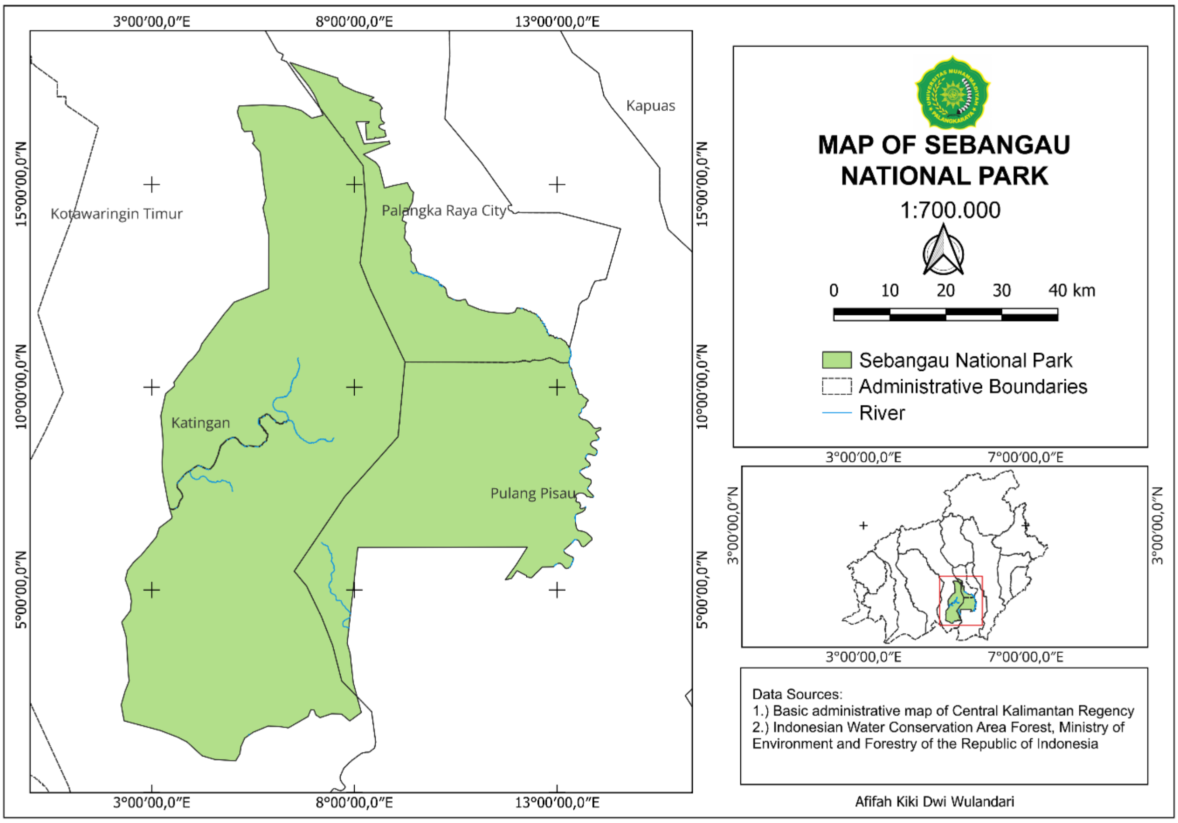

Figure 1. Research Location

Data and Software

The spatial data utilized in this study encompassed several sources, including Landsat-8 imagery captured in 2015, the Sebangau National Park area, and base maps (Table 1). The study employed Google Earth Engine and Quantum GIS software.

Table 1. Research data

Data	Scale/Resolution	Source
Landsat-8 imagery	30 meter	https://developers.google.com/earth-engine
National Sebangau Park	1:250.000	Ministry of Forestry of the Republic of Indonesia
Base map	1:250.000	Geospatial Information Agency of the Republic of Indonesia

Research Procedure

The general process of data analysis can be represented by a flow chart (Figure 2).

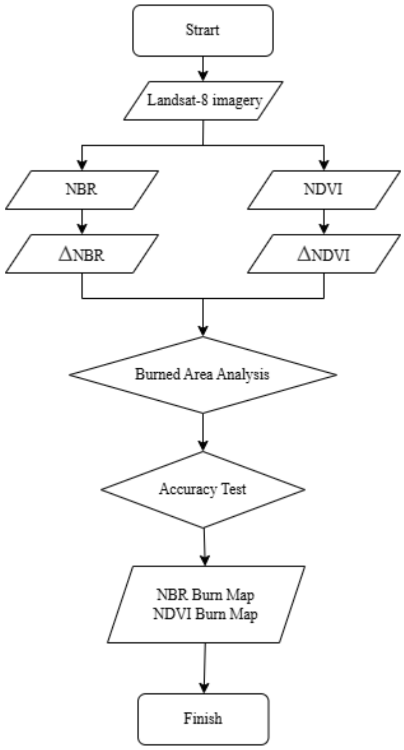

Figure 2. Research flow chart

The research employed the Normalized Burn Ratio (NBR) and the Normalized Difference Vegetation Index (NDVI) indices. The NBR is a standard tool used to identify areas that have been affected by fire. This method utilizes the Near Infrared (NIR) and Short Wavelenght Infrared (SWIR) segments of the electromagnetic spectrum (García et al., 1991) with the equation used:

$$NBR = \frac{NIR + SWIR}{NIR - SWIR}$$

The subsequent step in the methodology is to identify the level of land openness. This is accomplished by calculating the difference in NBR values using the following formula:

$$\Delta NBR = NBR_{t1} - NBR_{t2}$$

where NBR_{t1} is NBR before fire and NBR_{t2} is NBR after fire. The ΔNBR values are divided into two classes of burnt and unburnt areas. The values were determined based on equal interval classification. Nilai ΔNBR value less than 0.47 indicates a burnt area, while a value greater than 0.47 indicates a non-burnt area.

The Normalized Difference Vegetation Index (NDVI) is a vegetation index frequently employed to assess the density, greenness, and vegetation density of an area. The equation used (Philiani et al., 2016):

$$NDVI = \frac{NIR + RED}{NIR - RED}$$

The value of this index ranges from -1 (non-vegetation) to 1 (vegetation). The presence of dead or unhealthy vegetation is reflected in a greater amount of red waves and a smaller amount of near infrared (Andini et al., 2018). The standard deviation of the green vegetation variable is 0.2–0.8 (Que et al., 2019). The subsequent step in the methodology is to identify the level of land openness. This is accomplished by calculating the difference in NDVI values using the following formula:

$$\Delta NDVI = NDVI_{t1} - NDVI_{t2}$$

where $NDVI_{t1}$ is NDVI before fire and $NDVI_{t2}$ is NDVI after fire. The $\Delta NDVI$ values are divided into two classes of burnt and unburnt areas. The values were determined based on equal interval classification. Nilai $\Delta NDVI$ value less than 0.62 indicates a burnt area, while a value greater than 0.62 indicates a non-burnt area.

The accuracy of the prediction results for detecting burned and unburned areas based on NBR and NDVI values is tested. The accuracy test compares the results of index detection with those of interpretation delineation. The accuracy test uses the following equation (Foody, 2002). Accuracy tests are commonly used to evaluate map accuracy (Iskandar et al., 2025; Putri et al., 2025).

$$OA = \frac{\sum_{i=1}^{r} X_{ii}}{N}\ 100\%$$

$$KA = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+}X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+}X_{+i})}\ 100\%$$

RESULTS and DISCUSSION

Hotspot Distribution in Sebangau National Park

A hotspot is defined as a pixel in satellite imagery that shows an extremely high temperature and is associated with an active fire on the Earth's surface (Putra et al., 2019). Between 2015 and 2019, the analysis shows that the area affected by forest and land fires in Indonesia reached around 4.69 million hectares, which is equivalent to 2.5% of the country's total area. Kalimantan experienced the greatest impact of this total, with around 1.7 million hectares burned (Arisman, 2020). Significant changes in the distribution of hotspots in Sebangau National Park were seen from June to October 2015, with a peak of 581 hotspots recorded in October. This indicates that there was a high-intensity fire that month. The analysis revealed that the hotspot distribution tended to be low in June and increased sharply in September and

October (Figure 3). Figure 4 shows the spatial distribution of fire hotspots in Sebangau National Park.

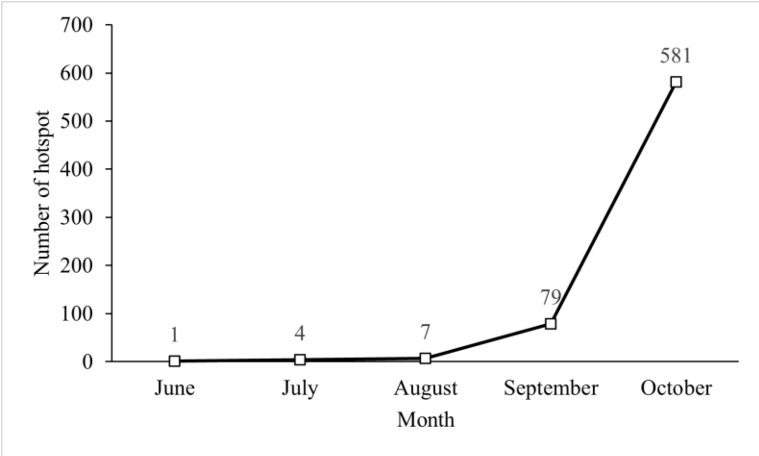

Figure 3. Number of Hotspots in 2015

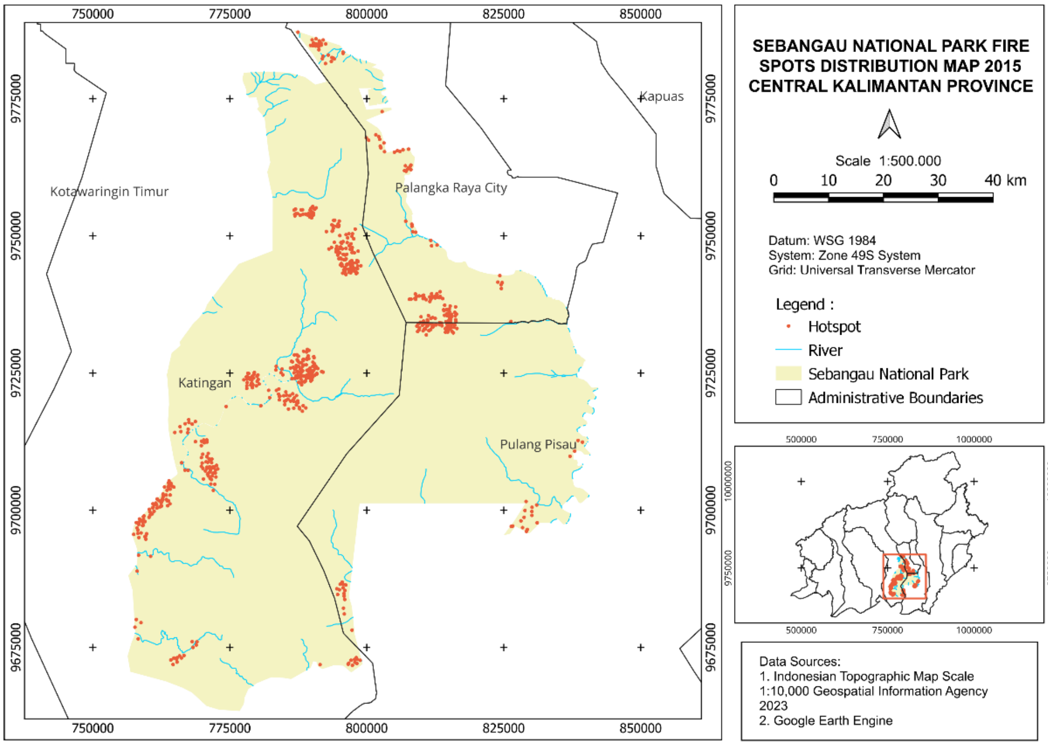

Figure 4. Map of hotspots in 2015

The 2015 increase in hotspots is related to the El Niño phenomenon. Research shows that the spread of hotspots increased dramatically in October 2015 (Qadri et al., 2023). This spike occurred when the dry season took place in conjunction with a strong El Niño. This assertion is consistent with the findings of research conducted by (Yananto et al., 2016), which demonstrated that this phenomenon led to a decline in rainfall intensity across several regions in Indonesia, particularly from July to October 2015. Consequently, the number of hotspots exhibited a substantial increase during this period, with a predominant distribution in the provinces of South Sumatra and Central Kalimantan.

Detection of Burned Areas According to NBR and NDVI

Preliminary findings from the analysis of forest fires using the NBR index in Sebangau National Park indicate that the area affected by fires encompasses 27,567.92 hectares, while the area that remained untouched by fire activity spans 509,750.14 hectares, as depicted in Figure 5. The data indicates that the majority of the Sebangau National Park area was not affected by fires, with the burned area constituting approximately 5.13% of the total area (Figure 6). This finding suggests that, despite the occurrence of fires, their spatial impact remained comparatively constrained when viewed in the context of the entire study area. The NBR algorithm, when employed on satellite images, has proven to be an effective tool for mapping and assessing the severity of forest and land fires. The decrease in NBR value has been shown to directly correlate with the level of vegetation damage after a fire, thus serving as an accurate indicator to assess the impact of fire on ecosystems (Arrafi et al., 2022).

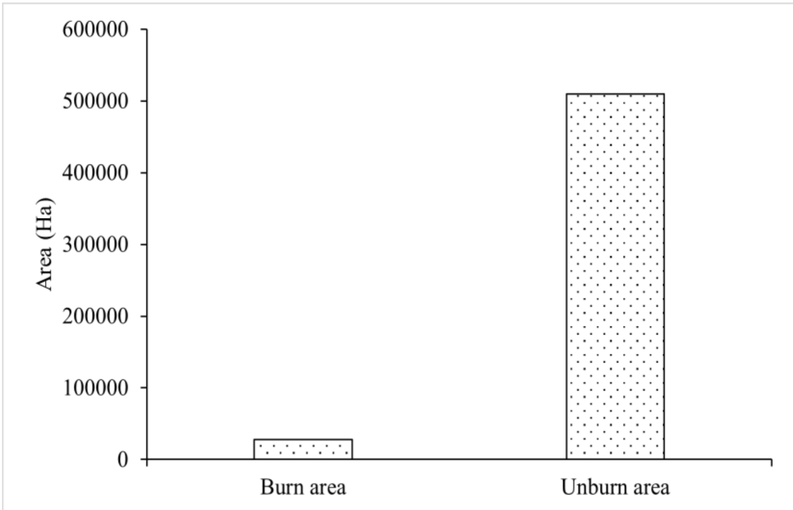

Figure 5. Burned area based on NBR index

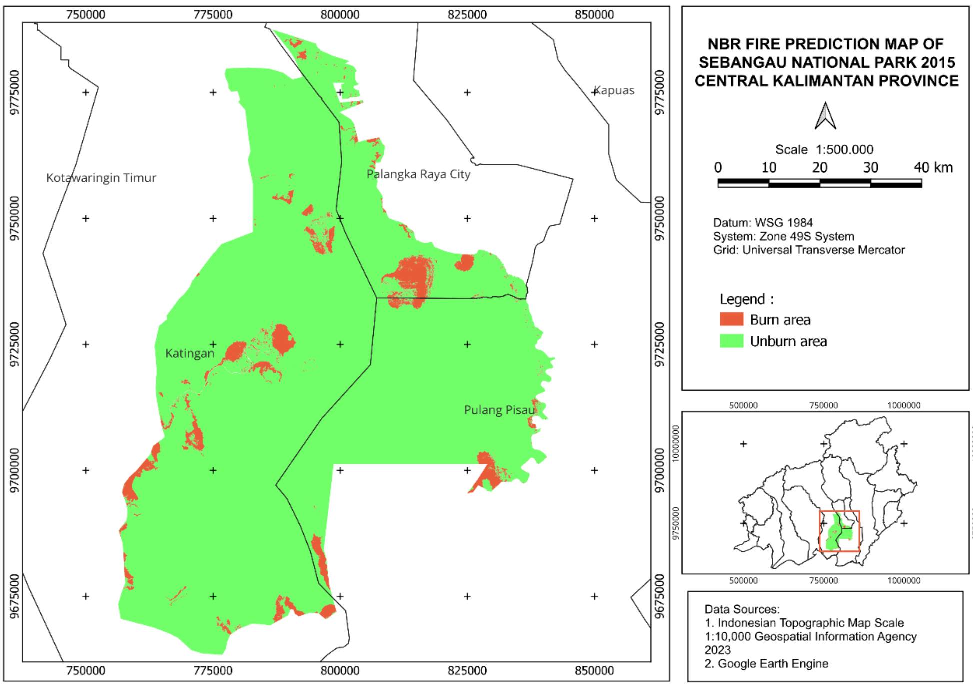

Figure 6. NBR burn map in 2015

The results of the analysis conducted using the NDVI index demonstrated that the area that experienced changes in vegetation due to fires reached 35,163.44 ha, while the area that remained unaffected was 502,163.40 ha (Figure 7). This indicates that approximately 6.54% of the total Sebangau National Park area experienced a substantial decline in vegetation, as illustrated in Figure 8. The decline in NDVI is not solely attributed to conflagrations; other factors, including drought, anthropogenic pressure, and land cover change, also play a role. As stated by (Khalwani et al., 2015), the Normalized Difference Vegetation Index (NDVI) can be utilized to discern alterations in vegetation resulting from fire events. A statement from the Sebangau National Park Center itself notes that fire patterns in the area are often linked to the dry season and human activities, which accelerate vegetation degradation.

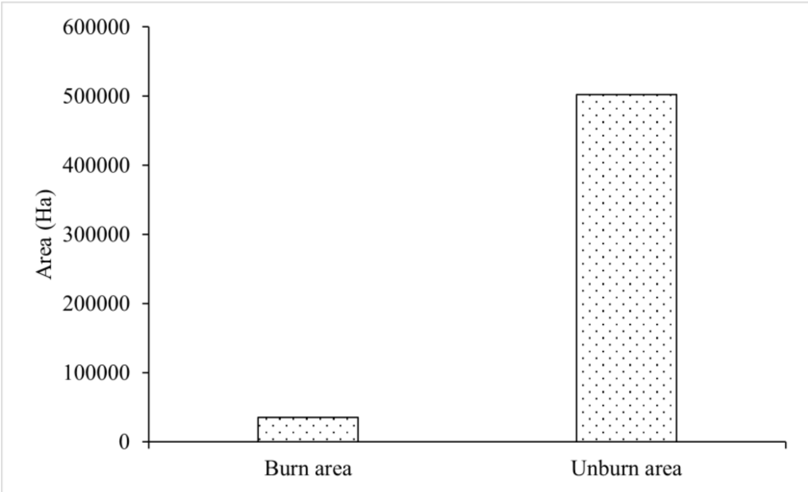

Figure 7. Burned area based on NDVI index

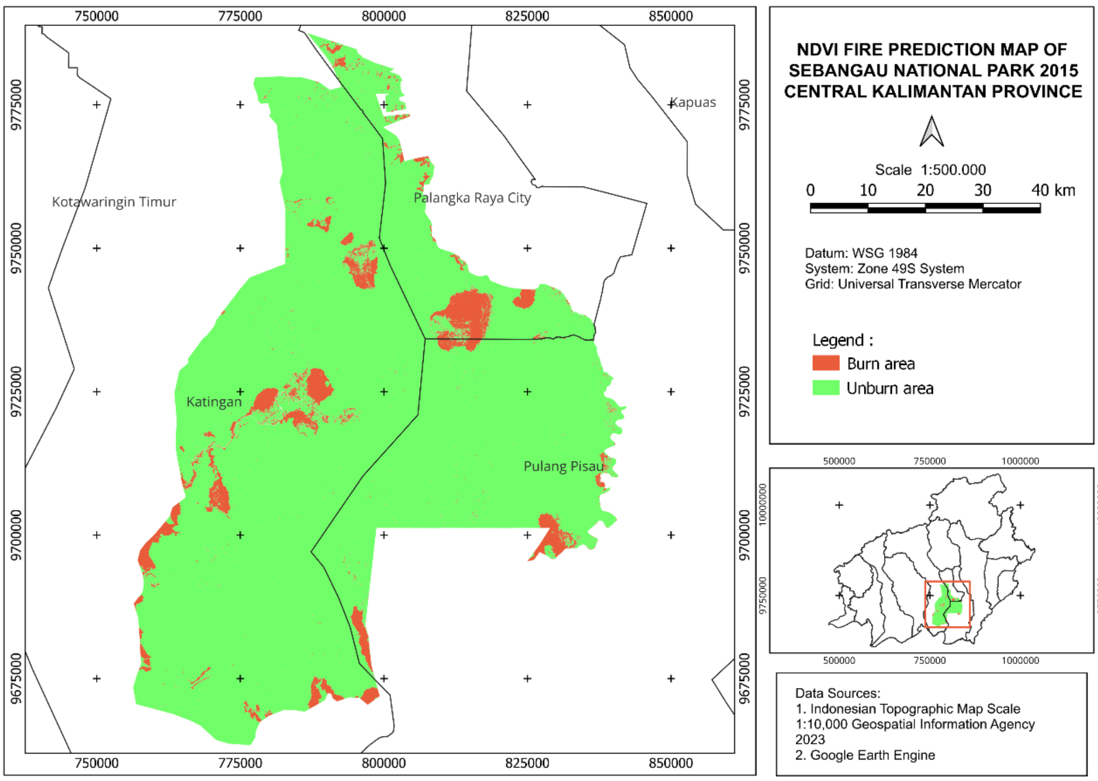

Figure 8. NDVI burn map in 2015

Accuracy Test

The results of the accuracy test conducted on NDVI in 2015 indicate that the Overall Accuracy (OA) value is 97.71%, and the Kappa Accuracy (KA) value is 81.46%. Similarly, the NBR in 2015 received an Overall Accuracy (OA) value of 97.69% and a Kappa Accuracy (KA) value of 79.22%, as illustrated in Table 2. According to (Foody, 2002) this accuracy is classified as good from the perspective of the KA coefficient. The Normalized Difference Vegetation Index (NDVI) is a metric that quantifies the reflectance of leaf chlorophyll, thereby enabling more precise detection of vegetation loss due to fire. A study by (Delgado-Moreno et al., 2021) demonstrated that the accuracy of the NDVI was 84.31%, which is significantly higher than the accuracy of other methods. Conversely, NBR, which utilizes the SWIR band to detect moisture content, frequently fails to accurately identify burned areas obscured by clouds or exhibiting minimal fluctuations in surface reflectance, as evidenced in the study (Dini et al., 2022) with an accuracy of 47.06%. This finding suggests that NDVI is more sensitive in identifying post-fire vegetation loss, even when it is not clearly visible to NBR monitoring.

This finding is of critical importance in the context of wildfire management and vegetation recovery strategies. The high accuracy of NDVI in detecting vegetation loss indicates that this index is more reliable for providing an accurate picture of post-fire ecosystem conditions, especially in areas covered by clouds or thin smoke. As (Congalton et al., 2019) have articulated, achieving high accuracy in the production of classifications is indispensable for substantiating spatial-based decision-making processes. The utilization of low-accuracy methodologies, such as the NBR under specific circumstances, as the foundation for planning, engenders a considerable risk of underestimating the affected area. This, in turn, can impede the efficacy of the rehabilitation program. Furthermore, the selection of indices that are less sensitive to vegetation change may result in the misallocation of resources. Therefore, the utilization of NDVI as the principal instrument in post-fire monitoring, or its integration with other indices in a multi-index approach as proposed by (Sharma et al., 2022), constitutes a strategic measure to ensure the precision of data employed in damage evaluation and environmental recovery planning.

Table 2. Accuracy test

Description	Accuracy (%)
OA NDVI	97,71
OA NBR	97,69
KA NDVI	81,46
KA NBR	79,22

Source: Research calculation results (2025)

CONCLUSION and RECOMMENDATION

The study concluded that the burnt area was 27,567.92 ha with the NBR index and 35,163.44 ha in Sebangau National Park. The NDVI index demonstrated a high degree of accuracy in comparison with the NBR index. Consequently, the results of this study can be employed as a reference in the context of fire mitigation and post-fire rehabilitation efforts within Sebangau National Park.

REFERENCES

Andini, S. W., Prasetyo, Y., & Sukmono, A. (2018). Analisis Sebaran Vegetasi dengan Citra Satelit Sentinel Menggunakan Metode NDVI dan Segmentasi. *Jurnal Geodesi Undip*, *7*(1), 14–24. doi: 10.14710/jgundip.2017.19295

Arisman, A. (2020). Analisis Tren Kebakaran Hutan dan Lahan di Indonesia Periode Tahun 2015-2019. *Jurnal Sains Teknologi Dan Lingkungan*, *6*(1), 1–9. doi: 10.29303/jstl.v6i1.109

Arrafi, M., Somantri, L., & Ridwana, R. (2022). Pemetaan Tingkat Keparahan Kebakaran Hutan dan Lahan Menggunakan Algoritma Normalized Burn Ratio (NBR) Pada Citra Landsat 8 di Kabupaten Muaro Jambi. *Jurnal Geosains Dan Remote Sensing*, *3*(1), 10–19. doi: 10.23960/jgrs.2022.v3i1.68

Congalton, R. G., & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices* (3rd Edition). CRC press. doi: 10.1201/9780429052729

Delgado-Moreno, D., & Gao, Y. (2021). Forest Degradation Estimation Through Trend Analysis of Annual Time Series NDVI, NDMI and NDFI (2010–2020) Using Landsat Images. *International Conference on Geospatial Information Sciences*, 149–159. doi: 10.1007/978-3-030-98096-2_11

Dini, N. L. K., Jauhari, A., & Rachmawati, N. (2022). Prediksi Nilai Karbon yang Hilang Akibat Kebakaran Hutan dan Lahan di Kota Banjarbaru. *Jurnal Sylva Scienteae*, *5*(3), 372–378. doi: 10.20527/jss.v5i3.5708

Dong, J., Xiao, X., Menarguez, M. A., Zhang, G., Qin, Y., Thau, D., Biradar, C., & Moore III, B. (2016). Mapping Paddy Rice Planting Area in Northeastern Asia with Landsat 8 Images, Phenology-Based Algorithm and Google Earth Engine. *Remote Sensing of Environment*, *185*, 142–154. doi: 10.1016/j.rse.2016.02.016

Farhadi, H., Managhebi, T., & Ebadi, H. (2022). Buildings Extraction in Urban Areas Based on the Radar and Optical Time Series Data Using Google Earth Engine. *Scientific-Research Quarterly of Geographical Data (SEPEHR)*, *30*(120), 43–63. doi: 10.22131/sepehr.2022.251053Abstract

Foody, G. M. (2002). Status of Land Cover Classification Accuracy Assessment. *Remote Sensing of Environment*, *80*(1), 185–201. doi: 10.1016/S0034-4257(01)00295-4

García, M. J. L., & Caselles, V. (1991). Mapping Burns and Natural Reforestation Using Thematic Mapper Data. *Geocarto International*, *6*(1), 31–37. doi: 10.1080/10106049109354290

Iskandar, B., Khasanah, K., & Marlina, S. (2025). Model Forest and Land Fires in Kahayan Central Forest Management Unit. *Journal of Sylva Indonesiana*, *8*(01), 28–38. doi: 10.32734/jsi.v8i01.15995

Khalwani, K. M., Bahruni, B., & Syaufina, L. (2015). Nilai Kerugian dan Efektivitas Pencegahan Kebakaran Hutan Gambut (Studi Kasus di Taman Nasional Sebangau Provinsi Kalimantan Tengah). *Risalah Kebijakan Pertanian Dan Lingkungan Rumusan Kajian Strategis Bidang Pertanian Dan Lingkungan*, *2*(3), 214–229.

Ma, Y., Wu, H., Wang, L., Huang, B., Ranjan, R., Zomaya, A., & Jie, W. (2015). Remote Sensing Big Data Computing: Challenges and Opportunities. *Future Generation Computer Systems*, *51*, 47–60. doi: 10.1016/j.future.2014.10.029

Morrogh-Bernard, H., Husson, S., Page, S. E., & Rieley, J. O. (2003). Population Status of the Bornean Orang-utan (Pongo pygmaeus) in the Sebangau Peat Swamp Forest, Central Kalimantan, Indonesia. *Biological Conservation*, *110*(1), 141–152. doi: 10.1016/S0006-3207(02)00186-6

Philiani, I., Saputra, L., Harvianto, L., & Muzaki, A. A. (2016). Pemetaan Vegetasi Hutan Mangrove Menggunakan Metode Normalized Difference Vegetation Index (NDVI) di Desa Arakan, Minahasa Selatan, Sulawesi Utara. *Surya Octagon Interdisciplinary Journal of Technology*, *1*(2), 211–222.

Putra, I., Heryanto, E., Sopaheluwakan, A., Pradana, R. P., & Haryoko, U. (2019). Sebaran Spasial dan Temporal Titik Panas (Hotspot) di Indonesia dari Satelit MODIS dengan Metode Gridding. *Semin. Nas. Geomatika*, *3*(2007), 1123–1128.

Putri, A., Marcoleos, S., Pratama, Y., & Iskandar, B. (2025). Monitoring Land Cover Change Indicative Map of Social Forestry Area in Pulang Pisau Regency. *Jurnal Belantara*, *8*(1), 115–123. doi: 10.29303/jbl.v8i1.1081

Qadri, M. S. I., Rusmayadi, G., Priatmadi, B. J., & Adriani, D. E. (2023). Analisis Karakteristik Spasial dan Temporal Hotspot di Taman Nasional Sebangau Provinsi Kalimantan Tengah. *EnviroScienteae*, *19*(4), 87–92. doi: 10.20527/es.v19i4.17801

Que, V. K. S., Prasetyo, S. Y. J., & Fibriani, C. (2019). Analisis Perbedaan Indeks Vegetasi Normalized Difference Vegetation Index (NDVI) dan Normalized Burn Ratio (NBR) Kabupaten Pelalawan Menggunakan Citra Satelit Landsat 8. *Indonesian Journal of Computing and Modeling*, *2*(1), 1–7.

Rahmia, K. I. N., & Febrianti, N. (2020). Pemanfaatan Data Sentinel-2 untuk Analisis Indeks Area Terbakar (Burned Area). *Jurnal Penginderaan Jauh Indonesia Februari*, *2*(01), 1–6.

Sharma, L. K., Gupta, R., & Fatima, N. (2022). Assessing the Predictive Efficacy of Six Machine Learning Algorithms for the Susceptibility of Indian Forests to Fire. *International Journal of Wildland Fire*, *31*(8), 735–758. doi: 10.1071/WF22016

Yananto, A., & Dewi, S. (2016). Analysis of the 2015 El Nino Event and its Influence on the Increase of Hotspots in Sumatera and Kalimantan. *J Sains Tekno Modif Cuaca*, *17*(1), 11–19.

Zurqani, H. A., Post, C. J., Mikhailova, E. A., Ozalas, K., & Allen, J. S. (2019). Geospatial Analysis of Flooding from Hurricane Florence in the Coastal South Carolina Using Google Earth Engine. *In International Journal of Applied Earth Observation and Geoinformat*, *69*.