*Research Article*

# Data Indo InaFire: Spatial Visualization of Peatland Fire Impact and Ecosystem Restoration Monitoring in PHU Jambi using Earth Engine Apps and Sentinel-2 MSI Imagery

## *Data Indo InaFire: Visualisasi Spasial Tingkat Keparahan Kebakaran Gambut dan Keberhasilan Restorasi Ekosistem di KHG Jambi Menggunakan Earth Engine Apps dan Citra Sentinel-2 MSI*

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***Abstract:*** Peatlands formed from long-term accumulation of partially decomposed organic matter in wetland areas. This particular ecosystem is not only capable of sequestering significant quantities of carbon but also vulnerable to forest and land fires (*karhutla*). Peatland produces considerable $CO_2$ emissions during fire occurrences, which consequently requires spatiotemporal monitoring to sustain its ecological roles and functions. This study aims to map the severity of fires in peatland ecosystems, estimate the success of post-fire restoration, and develop an Earth Engine Apps-based monitoring platform for peatland fire monitoring. Fire severity assessment and post-fire restoration success estimation were conducted in Jambi's Peat Hydrological Unit (PHU) in 2019 using the Normalized Burn Ratio (NBR) index derived from Sentinel-2 MSI satellite imagery. Most of Jambi PHU's fire severity and restoration levels are high. The area of PHU Jambi with high fire severity was 7,822.91 hectares, while the area with high restoration success was 23,744.69 hectares. NBR monitoring in PHU Jambi can be used to detect fire severity and restore success. The visualization of forest and land fire severity was successfully displayed on the Data Indo InaFire webGIS platform, an Earth Engine Apps-based monitoring platform.

*Keywords: Peatland, GEE, PHU, Jambi, NBR*

***Abstract:*** Lahan gambut terbentuk akibat akumulasi bahan organik yang terdekomposisi sebagian di wilayah lahan basah dalam jangka panjang. Ekosistem ini tidak hanya mampu menyerap sejumlah besar karbon tetapi juga rentan terhadap kebakaran hutan dan lahan (karhutla). Lahan gambut menghasilkan emisi $CO_2$ yang signifikan saat kejadian kebakaran, sehingga diperlukan pemantauan spasial dan temporal untuk mempertahankan peran dan fungsi ekologisnya. Penelitian ini bertujuan untuk memetakan tingkat keparahan kebakaran pada ekosistem gambut, mengestimasi keberhasilan restorasi pasca-kebakaran, serta mengembangkan platform pemantauan berbasis Earth Engine Apps untuk pemantauan kebakaran gambut. Penilaian tingkat keparahan kebakaran dan estimasi keberhasilan restorasi pasca-kebakaran dilakukan di Kesatuan Hidrologis Gambut (KHG) Jambi pada tahun 2019 menggunakan indeks Normalized Burn Ratio (NBR) yang diperoleh dari citra satelit Sentinel-2 MSI. Sebagian besar tingkat keparahan kebakaran dan tingkat keberhasilan restorasi di KHG Jambi tergolong tinggi. Luas wilayah KHG Jambi dengan tingkat keparahan kebakaran tinggi mencapai 7.822,91 hektar, sedangkan luas wilayah dengan tingkat keberhasilan restorasi tinggi mencapai 23.744,69 hektar. Pemantauan NBR di KHG Jambi dapat digunakan untuk mendeteksi tingkat keparahan kebakaran dan keberhasilan restorasi. Visualisasi tingkat keparahan kebakaran hutan dan lahan berhasil ditampilkan pada platform webGIS Data Indo InaFire, sebuah platform pemantauan berbasis Earth Engine Apps.

Kata kunci: Gambut, GEE, KHG, Jambi, NBR

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## INTRODUCTION

Peatlands formed from long-term accumulation of partially decomposed organic matter in wetland areas, which is capable of sequestering significant quantities of carbon. According to Saragi-Sasmito et al. (2019), peat soil can store up to 93% carbon. As much as 3% of the land area inclusively is estimated to be able to store 500-700 Gt of organic carbon on a global scale (Septian et al. 2023). Therefore, peat conservation has the potential to mitigate climate change (Harrison et al. 2020; Humpenöder et al. 2020). One of the problems in peat ecosystems is that they are vulnerable to forest and land fires (karhutla; Saharjo 2023). Peat ecosystems damaged by forest and land fires cause large amounts of stored carbon to be released, which exacerbates global warming and impacts climate change (Ward et al. 2007).

Remote sensing technology has become an critical tool for monitoring and modelling environmental dynamics, providing valuable information across diverse applications. The remote sensing-based information system has been extensively employed in monitoring peatlands (Du et al. 2019; Ghazaryan et al. 2016; Mahrad et al. 2020; Saputri et al. 2024A; Zhao et al. 2023), natural disasters (Nugraha et al. 2024; Scheip and Wegmann 2021), agriculture (Zhang et al. 2020), mangrove carbon stock (Adni et al. 2024), forest farmer safety management (Rahmawati et al. 2023), mining reclamation (Alamako et al. 2024), and coastal change (Madinu et al. 2024). In peatland ecosystems, monitoring systems are particularly vital for preventing and mitigating the adverse effects of fires. These systems enable the concurrent detection, tracking, and analysis of fire events. According to Minasny et al. (2019), Humpenöder et al. (2020), and Surahman et al. (2019), fire monitoring technologies aim to implement prevention strategies targeting both surface vegetation and subsurface peat fires. The delta Normalized Burn Ratio (dNBR) is a widely used method for analyzing fire-affected areas and quantifying fire severity using satellite imagery (Miller 2009). Initial assessments of fire severity are crucial for understanding trends and informing effective management strategies for Peat Hydrological Unit (PHU) landscapes (Saputri et al. 2024B; Sutikno et al. 2020; Pratama et al. 2023; Cahyono et al. 2022).

PHU Jambi was chosen due to its relevance as a large peat ecosystem area prone to fires, for example in August 2019, 810 hotspots were detected in Jambi Province (Saputra et al. 2021). The Jambi PHU in 2019 experienced significant fires with a burned area of 33,863.6 ha, mostly in forest areas. This condition emphasizes the importance of monitoring and special handling efforts in PHU Jambi to maintain its function in climate change mitigation. One of the efforts that can be made to monitor peat ecosystem areas is the use of remote sensing technology and Geographic Information Systems (GIS). In addition, it is necessary to develop a remote sensing-based monitoring system for monitoring PHU conditions related to forest and land fires. Therefore, this research aims to analyze and map the severity of fires in PHU Jambi, estimate the success rate of post-fire restoration in PHU Jambi and develop a monitoring platform based on Earth Engine Apps for visualization in monitoring fires in peat ecosystems.

## MATERIALS AND METHODS

### Study Location

The study site is located in PHU located in Jambi province, Indonesia. The PHU area boundaries were obtained from map from Low Carbon Development Indonesia (LCDI) of the Ministry of PPN-Bappenas (LCDI 2019). The study location map is shown in Figure 1. The PHU is located in the administrative areas of East Tanjung Jabung and Muaro Jambi. In addition, the PHU also contains a conservation area, namely Berbak National Park.

### Data Source and Research Workflow

This research used Sentinel-2 MultiSpectral Instrument (MSI) imageries obtained directly from the Google Earth Engine (GEE) platform. In this study, sentinel-2 type surface reflectance (SR) was used with acquisition time from December 2018 to August 2019 for pre-fire imagery, September 2019 to November 2019 for post-fire imagery and January 2023 to December 2023 for regrowth imagery. The cloud masking process uses the GEE platform with a selection of cloud percentages of less than 30%. The selection of satellite imagery is based on the median of the acquisition period range. Sentinel images are processed in Google Earth Engine (GEE) to obtain land cover classification, severity of forest and land fires and post-fire ecosystem recovery. The research flowchart is presented in Figure 2.

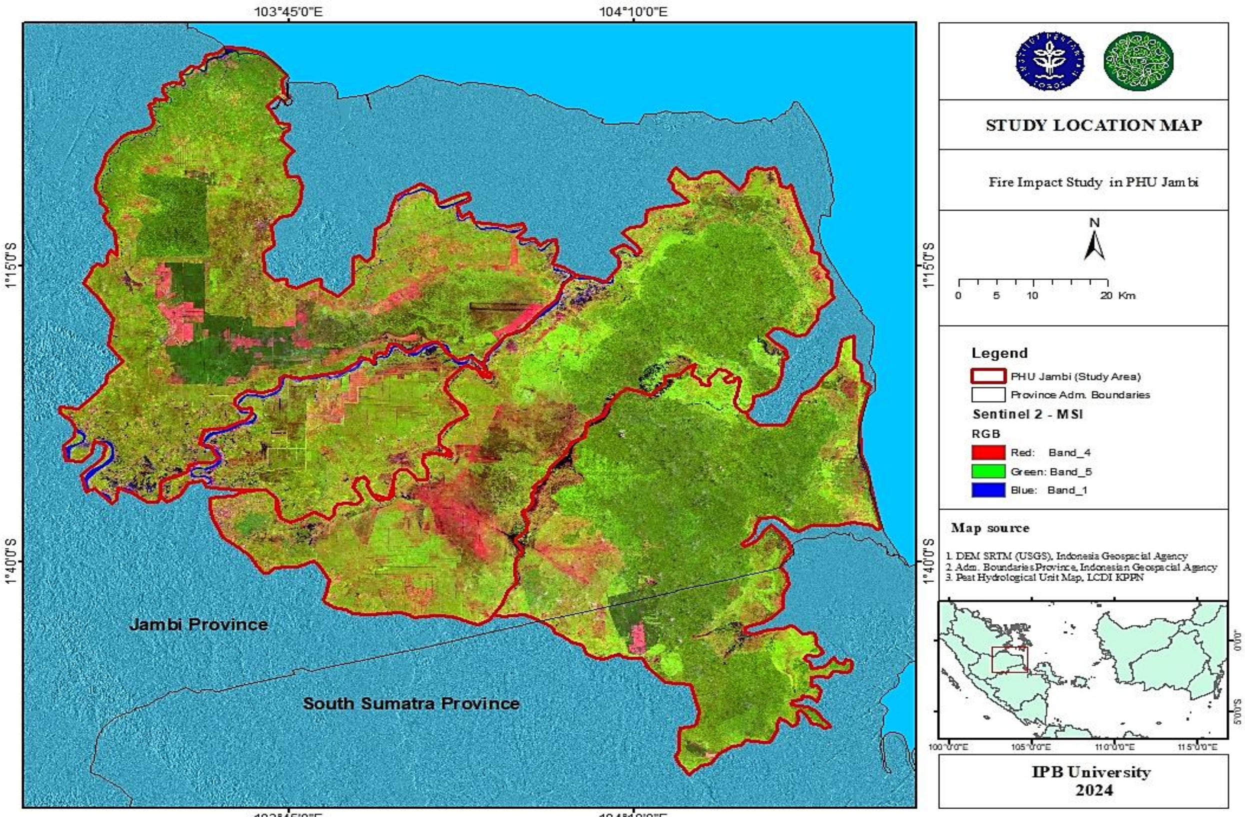


**Figure 1.** Study location Map

## Data Processing and Analyses

### *LULC Classification*

Land classification was conducted using a supervised classification method involving several indices, namely vegetation, water, and built-up indices (Table 1). This study employed a random forest/RF classifier, a machine learning algorithm composed of fully grown decision trees that were built by performing random resampling both on input variables and observations (Breiman 2001; Ho 1998). RF classifiers were reportedly able to handle high data dimensionality and multicollinearity (Belgiu and Drăguţ 2016), which can solve both classification and regression problems (Sheykhmousa et al. 2020). In the study, we tuned the RF algorithm using tree = 500 and training data up to 582688 data for forests, 12062 for plantations, 185 data for built-up land, 834 data for water bodies, 13756 data for plantation forests, and 12062 data for bare land. Accuracy assessments were performed using overall accuracy and kappa accuracy methods. The land classification process is based on the spectral index bands as its input dataset. According to Asy'ari et al 2023, the use of multiple indices in land cover classification could enhance classification accuracy by leveraging the high sensitivity of each index to land cover types.

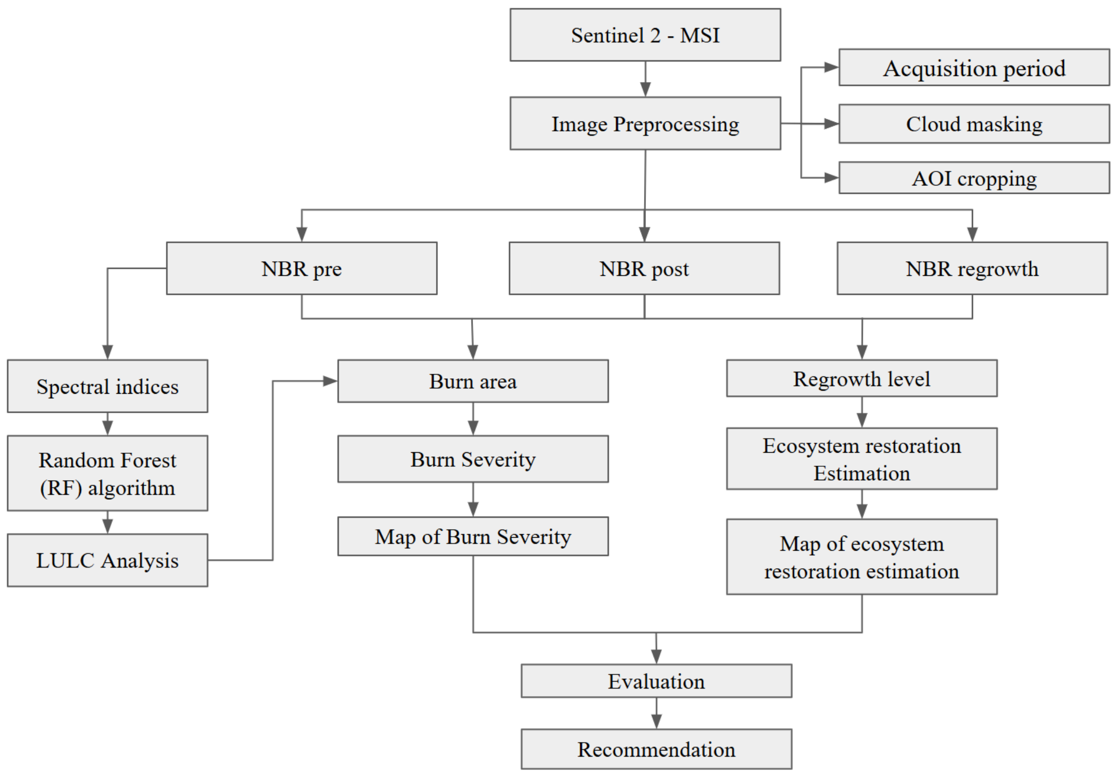


**Figure 2.** Research workflow employed in this study

**Table 1.** Spectral index input dataset from land use classification

| Index | Formula | References |
|---|---|---|
| Atmospherically Resistant Vegetation Index (ARVI) | ARVI = (NIR – (2 Red) + Blue) / (NIR + (2 x Red) + Blue) | Kaufman and Tanre (1992) |
| Chlorophyll Absoption Ratio Index (CARI) | CARI = ((RE – Red) – 0,2 x (RE – Green)) x (RE – Red) | Kim et al (1994) |
| Enhanced Vegetation Index (EVI) | EVI = 2.5 x ((NIR – Red) / ((NIR) + (C1 x Red) – (C2 x Blue) + L)) | Huete et al (2002) |
| Modified Chlorophyll Absorbtion Ratio Index (MCARI) | MCARI = ((NIR – Red) – 0,2 x (NIR – Green)) x (NIR – Red) | Daughtry (2000) |
| MNDVI (Modified Normalized Vegetation Index) | MNDVI = (c.NIR – RED)/(c.NIR+RED) | Jurgens (1997) |
| Soil Adjusted Vegetation Index (SAVI) | SAVI = ((NIR – Red) / (NIR + Red + L)) x (1 + L)<br>L = 0.5 | Huete (1988) |
| Specific Leaf Area Vegetation Index (SLAVI) | SLAVI = NIR / Red + MIR | Lymburner et al (2019) |
| Index-Based Built-up Index (IBI) | IBI = NDBI – ((SAVI + MNDWI) / 2) / NDBI + ((SAVI + MNDWI) / 2) | Xu (2008) |

| Index | Formula | References |
|---|---|---|
| Augmented Normalized Difference Water Indeks (ANDWI) | ANDWI = (Blue + Green + Red + NIR – SWIR1 – SWIR2) / (Blue + Green + Red + NIR + SWIR1 + SWIR2) | Rad et al (2021) |
| Land Surface Water Index (LSWI) | LSWI = NIR – SWIR1 / NIR + SWIR1 | Xiao et al (2002) |
| Modified Normalized Difference Water Index (MNDWI) | MNDWI = Green - SWIR / Green + SWIR | Xu (2006) |

**Information:** Blue: blue band; Green: green band; Red: red band, RE: red-edge band; NIR: near-infrared band; SWI: shortwave-infrared band; C1 C2: the aerosol coefficients were 6.0 and 7.5, respectively, G: gain factor (value 2.5); S2: Sentinel 2 MSI

### *Burn Area Detection*

Assessment of fire severity and estimation of post-fire restoration success was conducted using the NBR burn index. This data process was obtained from Sentinel-2 MultiSpectral Instrument (MSI) satellite imagery supported by Earth Engine Apps and ArcMap GIS 10.3 application. Fire and restoration data processing techniques use Geographic Information System (GIS) analysis with the help of ArcMap GIS 10.3 application. Earth Engine Apps is a derivative product of Google Earth Engine that has the function of visualizing the results of data analysis. Detection of burnt area, severity, and recovery rate was conducted using the Normalized Burn Ratio (NBR) index. NBR is a spectral index used in detecting the severity of forest and land fires because it uses SWIR bands that are sensitive to water or moisture (Naseri and Kalkan 2020). The NBR value is calculated from the difference between near Infrared/NIR and short-wave infrared/SWIR bands divided by the sum of the two (Santos et al. 2020), with Equation 1.

$$NBR = (NIR - SWIR)/(NIR+SWIR) \qquad \text{Equation (1)}$$

where
NBR : Spectral value of *Normalized Burn Ratio*
NIR : Band-8 Sentinel-2 MSI
SWIR : Band-11 Sentinel-2 MSI

The analysis of the extent and level of forest fires uses the delta NBR severity (dNBRs) approach, which is the difference between the pre and post NBR values (Santos et al. 2020). NBR pre is the result of analyzing land data before burning from December 2018 to August 2019, while NBR post is the result of analyzing land data that experienced fires from September to November 2019. The dNBRs approach was calculated using Equation 2.

$$dNBRs = NBR\ pre - NBR\ post \qquad \text{Equation (2)}$$

where
dNBRs : NBR value differences/delta
NBR *pre* : Spectral value NBR before forest and land fire
NBR *post* : Spectral value NBR after forest and land fire

The analysis of estimating restoration success was carried out using the delta NBR regrowth (dNBRr) approach, which is the difference between NBR post and NBR regrowth (Santos et al. 2020). NBR post is the result of data analysis of land that experienced fires from September to November 2019, while NBR regrowth is the result of data analysis of land that experienced recovery from January to December 2023. The dNBRr approach is calculated using Equation 3. Meanwhile, the estimation of fire severity and ecosystem recovery rate is based on the research (Santos et al. 2020) presented in Table 2.

$$dNBRr = NBR\ post - NBR\ regrowth \quad \text{Equation (3)}$$

where
dNBRr : Delta NBR regrowth
NBR *post* : Spectral value NBR after forest and land fire
NBR *regrowth* : Current NBR spectral value

**Table 2.** Burn severity and recovery level

| Severity and recovery level | Interval dNBR |
|---|---|
| Enhanced recovery high | -0-50 – (-0-25) |
| Enhanced recovery low | -0-25 – (-0-99) |
| Non-burnt | -0-10 – 0-99 |
| Low severity | 0-10 – 0-27 |
| Moderate low severity | 0-27 – 0-44 |
| Moderate severity | 0-44 – 0-66 |
| High severity | 0-66 – 0-13 |

### *Data Visualization using Earth Engine Apps*

Spatial data on peat fire severity was visualized using the Earth Engine Apps platform. This platform is a cloud computing-based geospatial platform that allows integration of satellite image data and can display the results of data analysis (Amani et al. 2020). The development of this platform was carried out with the help of JavaScript programming language with functions in displaying spatial data.

## RESULTS

### LULC Classification

The results of the land classification show that most of the land cover in KHG Jambi is forest. There are several other land covers such as plantations, industrial plantations, settlements, open land, and water bodies as shown in Figure 3. The figure shows that most of the burned areas are in forest land cover. This indicates that there is damage to the peat ecosystem in the forest area which has the potential to cause forest and land fires. The results of the accuracy assessment showed an overall accuracy value of 82.54% with a kappa statistic of 78.34%.

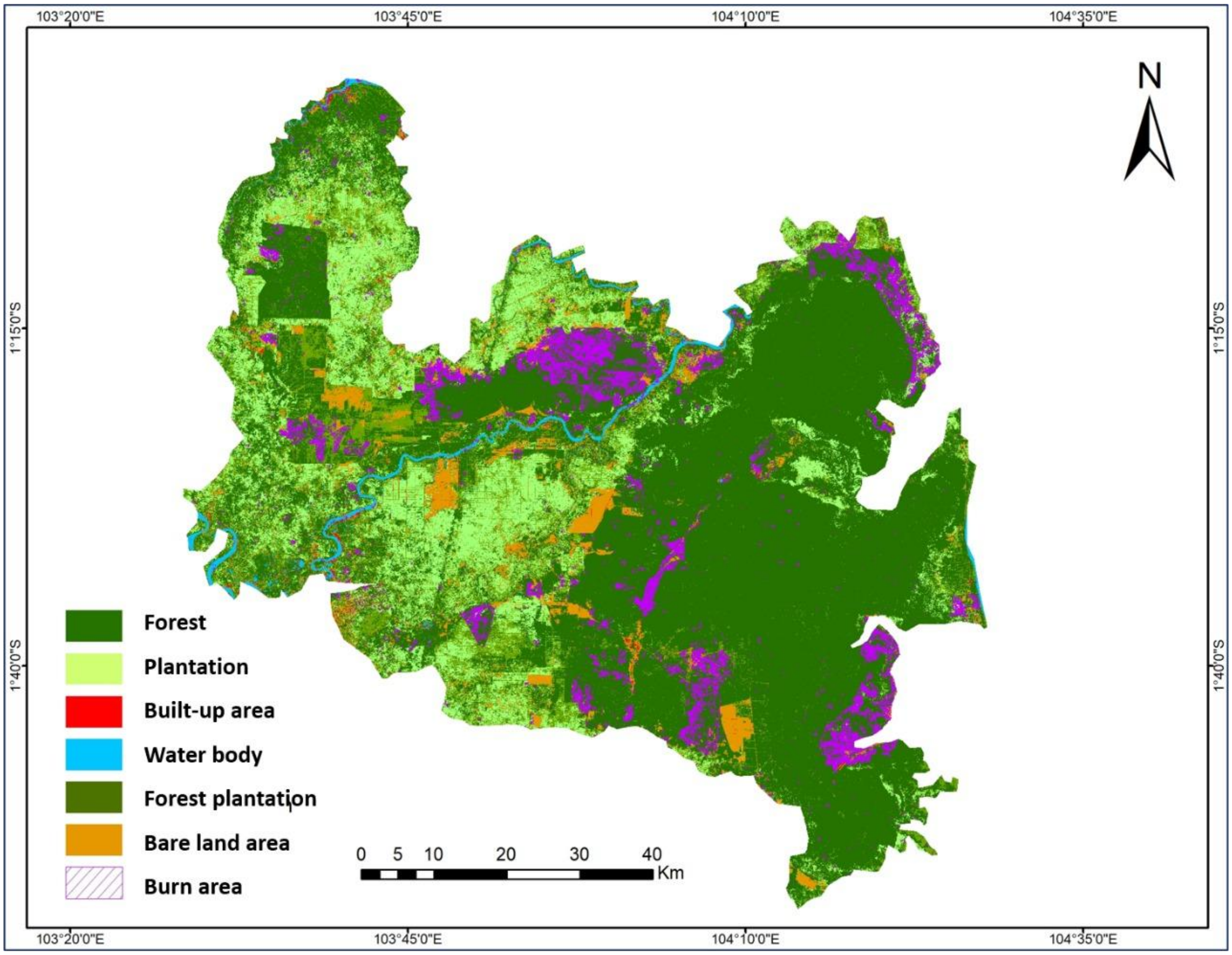


**Figure 3.** LULC classification and burn area

## Fire Peatland Impact

The severity of fires is reflected in the dNBRs and dNBRr analyses results, as shown in Figure 4. Higher dNBRs values indicated more severe fire levels, while lower dNBRr values were designated to better post-fire recovery. Most of the burnt areas were found in the forest area to the east, which were adjacent to the coastal areas. There were some burnt areas in the Berbak National Park area. Meanwhile, a small fraction of the burnt area occupied the plantation areas.

## Timeseries of Peatland Succession

The results of the NBR time series analysis showed that from September to December 2019 the NBR value has decreased drastically, proving that the month has occurred forest and land fires (Figure 5). Forest and land fires produced a relatively low NBR spectral values. NBR is particularly sensitive to soil moisture content due to the incorporation SWIR band (Equation 1), which exhibits low reflectance under high-water conditions (Roy et al. 2006).

The results of the analysis of fire severity and post-fire recovery are shown in Figure 6. The results show that most of the forest and land fires were classified as high in severity. However, the level of post-fire recovery is mostly categorized as high (Figure 7). Recovery from forest and land fires can come from natural succession or restoration programs carried out by communities.

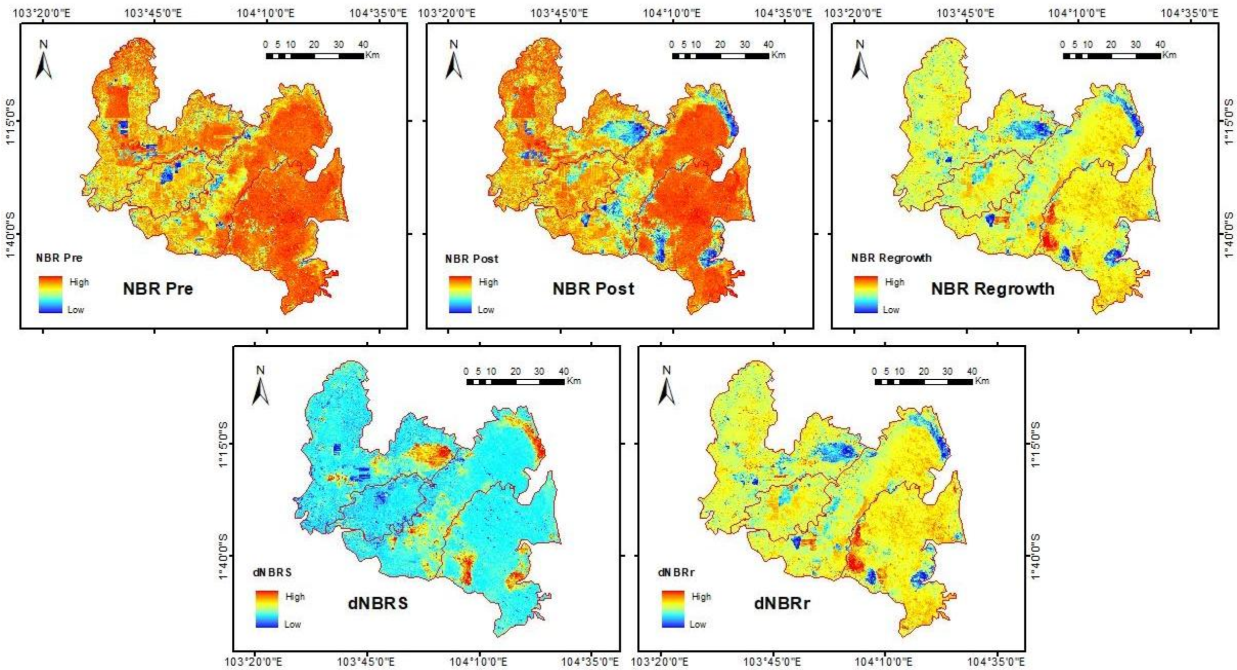


**Figure 4.** Visual of dNBR analysis

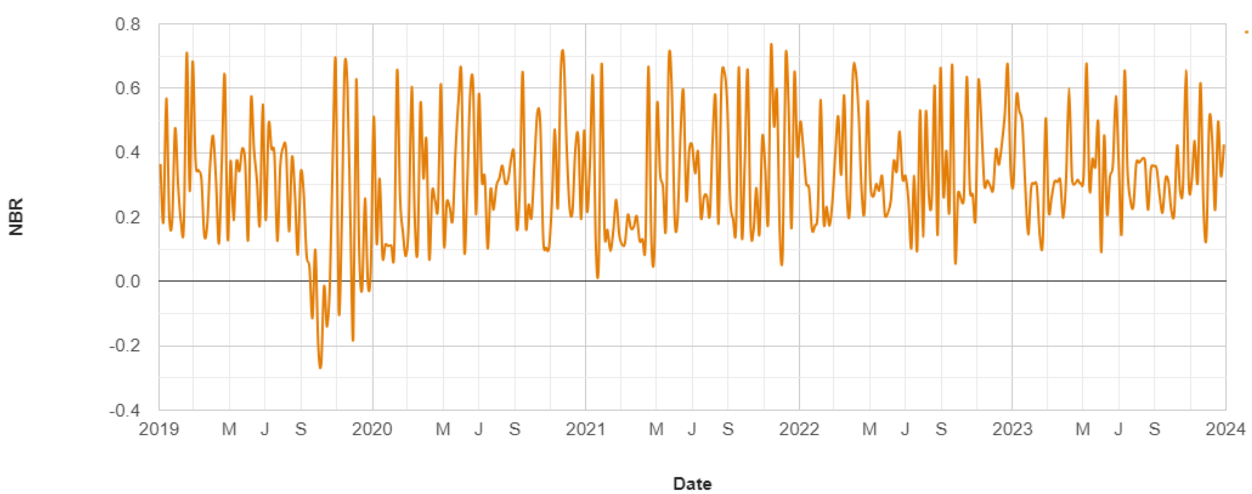


**Figure 5.** NBR Time Series in the Jambi PHU

## Platform InaFire: Indonesia Forest and Land Fire Monitoring

The visualization of forest and land fire severity is displayed in the Earth Engine Apps-based platform Data Indo InaFire (Figure 8). The platform can present land and forest fire data spatially for users. The platform displays Sentinel 2 satellite imagery visualized with composite

R-G-B, SWIR-NIR-Red bands. The platform includes a legend feature that shows the severity of the fire, a location feature that can select a target location. These features are built from existing functions in the Google Earth Engine using the JavaScript programming language.

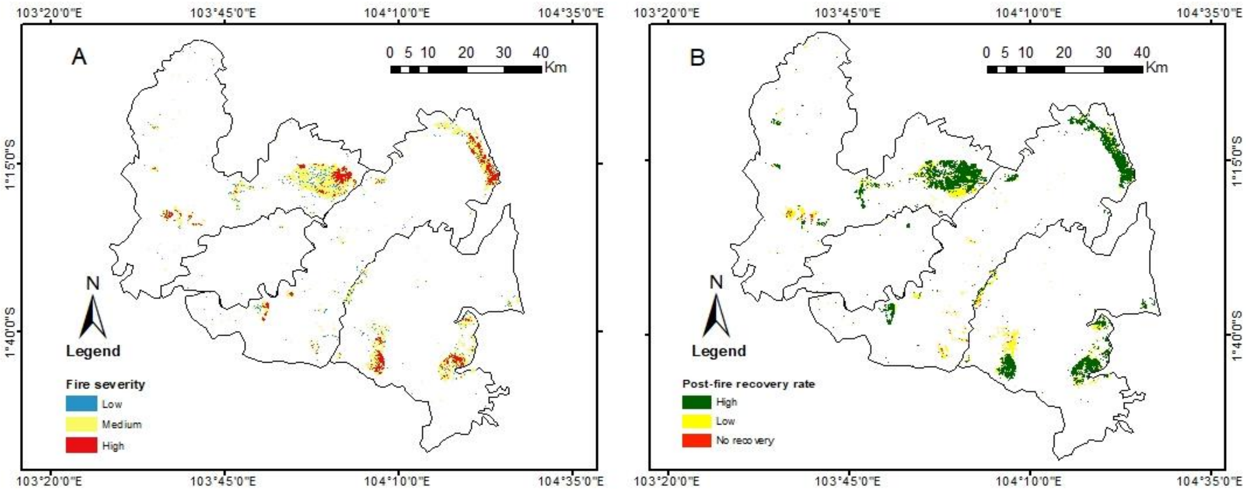


**Figure 6.** Map of burned area in KHG Jambi, (A) burn severity, (B) post-fire recovery rate

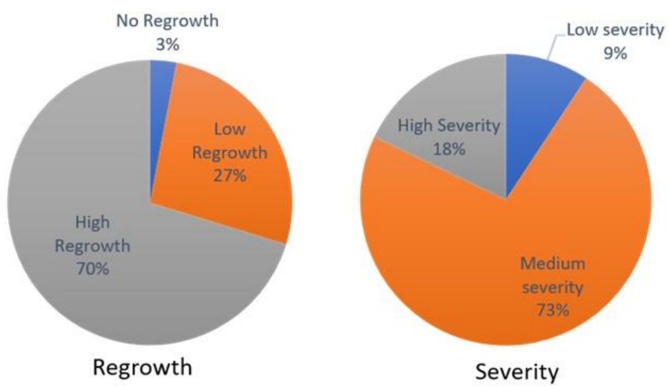


**Figure 7.** Area of fire severity and post-fire recovery rate

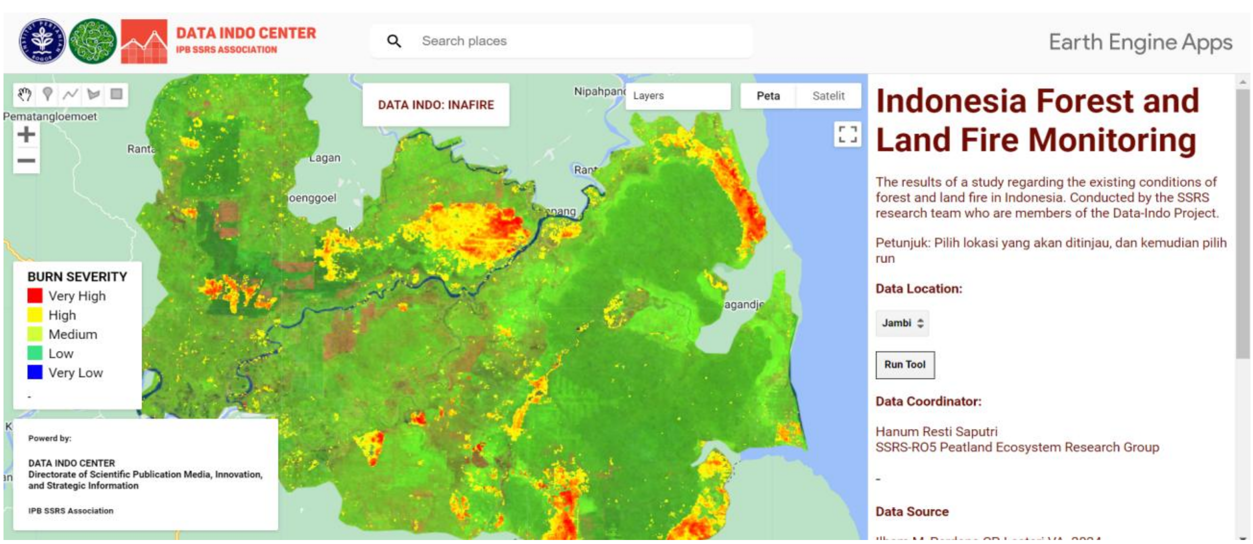


**Figure 8** Platform Data-Indo InaFire

## DISCUSSION

Burned areas were indicated by low NBR values, as fire-affected vegetations produced high SWIR reflectance and low NIR (Roy et al. 2021). Figure 4 clearly visualized this contrast, as burned areas appearing dark or dark red due to high dNBR values, reflecting considerable decreases in NBR due to forest and land fires. Time series data from September to December 2019 as exhibited in Figure 5, further confirmed this drastic decline in NBR values. The use of the NBR value in detecting burned areas can use the delta NBR (dNBR) approach, which is the difference between the pre NBR (before burning) and post NBR (after burning). The use of the dNBR value is more optimal in detecting burned areas while estimating the severity of burned areas (Escuin et al. 2008). NBR also successfully detects burned areas using segmentation algorithms with an overall accuracy value of 94% (Vedovato et al. 2015). Overlaying NBR-based fire detection with land-use and land-cover (LULC) analysis revealed that most burned areas are concentrated across forest land cover, including conservation areas such as the Berbak National Park, located at the Jambi-South Sumatra border (Figure 3). Based on a previous report (Widodo 2014), Jambi Province is one of the provinces that has a fairly high level of forest and land fire vulnerability. Meanwhile, forest and land fires in Jambi Province caused severe forest degradation and release considerable amount of $CO_2$ and particulate matter that is harmful to health (Sari et al. 2014).

Previous research by Teodoro and Ana (2019) and Rizqika et al (2012) demonstrated that NBR approach could accurately estimate forest and land fire severity in the field. The analysis of fire severity and recovery in PHU Jambi (shown in Figures 6 and 8) revealed that most areas experienced high levels of both fire severity and recovery. The total burned area in Jambi PHU was estimated at approximately 33,863.6 ha, of which 29,106.38 ha or 85.95% of the total area was located on forest land. The fire severity analysis showed that 4,067.41 ha fell under low-medium severity, 21,809.97 ha under upper-medium severity, and 7,822.91 ha under high severity. Post-fire restoration estimates for 2023 indicated that 23,744.69 ha had high recovery, 9,030.42 ha had low recovery, and 1,014.32 ha showed no recovery. This study findings on fire severity in Jambi PHU is aligned with Saputra et al (2021), who reported 810 hotspots in Jambi Province in 2019. Current and previous results highlighted the Jambi PHU's vulnerability to fires. The extensive burned area underscores the need for targeted management strategies in PHU Jambi. Developing a national-scale PHU monitoring platform is crucial to track burned areas and assess peat restoration success. Using NBR analysis with Sentinel-2 MSI imagery effectively detected fire severity and restoration outcomes in the peat ecosystem.

Furthermore, although the NBR approach employed in this study offers significant potential for monitoring peatland fires due to its strong capability in detecting burned areas, several limitations still persist. NBR has a high sensitivity to built-up land and open land, thus increasing detection bias, although the bias can be reduced by using dNBR (Picotte and Robertson 2011). However, the use of dNBR also has the potential for miss-classification of changes in land use, especially changes in vegetated areas to open land. Future advancements should focus on developing burned area detection methods using machine learning or other innovative approaches, alongside implementing robust accuracy assessment frameworks to enhance detection precision.

The severity of forest and land fires was successfully visualized through the Data Indo InaFire platform, an Earth Engine Apps-based monitoring system accessible at https://ee-dataindo-ssrs.projects.earthengine.app/view/inafire. This platform presented spatial data on forest and land fire severity and can be utilized to monitor such events across Indonesia. Designed for ease of use, it caters to users with limited GIS expertise. Leveraging cloud computing, the platform offered efficient data processing and had the potential to serve as a primary database for spatial information on forest and land fires in Indonesia. Similar to this study, Zhang et al. (2020) developed an Earth Engine Apps-based platform for agricultural land use monitoring, demonstrating the versatility of such systems while pinpointing opportunities for further enhancement.

## CONCLUSIONS

The analysis of burned areas in PHU Jambi using dNBR with Sentinel-2 MSI imagery demonstrated its effectiveness in detecting peat fire severity and restoration success in Jambi PHU. An approximate of 33,863.6 ha of burned area was estimated in total, with 85.95% (29,106.38 ha) located on forest land cover. Fire severity analysis categorized 4,067.41 ha as lower-medium severity, 21,809.97 ha as upper-medium severity, and 7,822.91 ha as high severity. Post-fire restoration success in 2023 showed 23,744.69 ha achieved high recovery, 9,030.42 ha showed low recovery, and 1,014.32 ha exhibited no recovery. The severity of forest and land fires was effectively visualized through the Data Indo InaFire platform, an Earth Engine Apps-based system, highlighting its potential as a national-scale tool for monitoring fire impacts and restoration outcomes.

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## REFERENCES

Adni SF, Asy'Ari R, Raihan F & Putra EI. 2024. Carbon stock estimation based on remote sensing in the northern coast of Java. *In IOP Conference Series: Earth and Environmental Science.* 1315:1-9. https://doi.org/10.1088/1755-1315/1315/1/012042

Alamako WB, Dzulfigar A, Asy'Ari R, Nurhawaillah LE, Raihan F, Pudjawati NH, Inanda IA, Pramestri AQ, Humanisa NH, Pratama OR, Saputra R, Setiawan Y, Zamany NP, Pramulya R. 2024. Mining Reclamation Monitoring using Sentinel-2 Temporal Data: Case Study in PT Adaro Energy Indonesia Mining Area. *SSRS Journal B: Spatial Research*, 2: 10-23. https://publishing.ssrs.or.id/ojs/index.php/ssrs-b/article/view/24

Amani M, Ghorbanian A, Ahmadi SA, Kakooei M, Moghimi A, Mirmazloumi SM & Brisco B. 2020. Google earth engine cloud computing platform for remote sensing big data applications: A comprehensive review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13:5326-5350. https://doi.org/10.1109/JSTARS.2020.3021052

Asy'Ari R, Ranti A, Rahmawati AD, Zulfajrin M, Nurazizah LL, Putra MCA, Khairunnisa ZN, Prameswari FA, Pramulya R, Zamani NP, Setiawan Y,& Sudrajat, A. 2023. High heterogeneity LULC classification in Ujung Kulon National Park, Indonesia: A study testing 11 indices, Random Forest, sentinel-2 MSI, and GEE-based cloud computing. *Celebes Agricultural*, 3(2): 82-99. https://doi.org/10.52045/jca.v3i2.381

Belgiu M & Drăguţ L. 2016. Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing,* 114: 24-31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Breiman L. 2001. Random forest. *Machine Learning*. 45(1):5–32. https://doi.org/10.1023/a:1010933404324

Cahyono BK, Aditya T, & Istarno. 2022. The Determination of Priority Areas for the Restoration of Degraded Tropical Peatland Using Hydrological, Topographical, and Remote Sensing Approaches. *Land*, 11(7): 1094. https://doi.org/10.3390/land11071094

Daughtry CS, Walthall CL, Kim MS, De Colstoun EB, & McMurtrey Iii JE. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote sensing of Environment, 74(2): 229-239. https://doi.org/10.1016/S0034-4257(00)00113-9

Du J, Watts JD, Jiang L, Lu H, Cheng X, Duguay C, Tarolli P. 2019. Remote sensing of environmental changes in cold regions: Methods, achievements and challenges. *Remote Sensing*. 11(16):1952. https://doi.org/10.3390/rs11161952

Duryat D & Darmawan A. 2019. Efisiensi penggunaan citra multisensor untuk pemetaan tutupan lahan. *Jurnal Sylva Lestari*, *7*(3):342-349. http://dx.doi.org/10.23960/jsl37342-349

Escuin S, Navarro R, & Fernández P. 2008. Fire severity assessment by using NBR (Normalized Burn Ratio) and NDVI (Normalized Difference Vegetation Index) derived from LANDSAT TM/ETM images. *International Journal of Remote Sensing*, 29(4): 1053-1073. https://doi.org/10.1080/01431160701281072

Harenda KM, Lamentowicz M, Samson M & Chojnicki BH. 2018. The role of peatlands and their carbon storage function in the context of climate change. *Interdisciplinary approaches for sustainable development goals: Economic growth, social inclusion and environmental protection*, 169-187.https://doi.org/10.1007/978-3-319-71788-3_12

Harrison ME, Ottay JB, D'Arcy LJ, Cheyne SM, Anggodo, Belcher C, van Veen FF. 2020. Tropical forest and peatland conservation in Indonesia: Challenges and directions. *People and Nature*, 2(1): 4-28. https://doi.org/10.1002/pan3.10060

Ho TK. 1998. The random subspace method for constructing decision forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 20(8):832–844. https://doi.org/10.1109/34.709601

Huete AR. 1988. A Soil Adjusted Vegetation Index (SAVI). *Remote Sensing of Environemt*. 25: 295-309. https://doi.org/10.1016/0034-4257(88)90106-X

Huete AR, Didan K, Miura T, Rodriguez EP, Gao X & Ferreira LG. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1-2): 195-213. https://doi.org/10.1016/S0034-4257(02)00096-2

Humpenöder F, Karstens K, Lotze-Campen H, Leifeld J, Menichetti L, Barthelmes A, & Popp A. 2020. Peatland protection and restoration are key for climate change mitigation. *Environmental Research Letters*, 15(10): 104093. https://doi.org/10.1088/1748-9326/abae2a

Ghazaryan G, Dubovyk O, Kussul N & Menz G. 2016. Towards an improved environmental understanding of land surface dynamics in Ukraine based on multi-source remote sensing time-series datasets from 1982 to 2013. *Remote Sensing*. 8(8):617. https://doi.org/10.3390/rs8080617

Jurgens C. 1997. The modified normalized difference vegetation index (mNDVI) a new index to determine frost damages in agriculture based on Landsat TM data. *International Journal of Remote Sensing*. 18(17): 3583-3594. https://doi.org/10.1080/014311697216810

Kaufman YJ & Tanre D. 1992. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote sensing*, 30(2): 261-270. https://doi.org/10.1109/36.134076

Kim MS. 1994. The use of narrow spectral bands for improving remote sensing estimations of fractionally absorbed photosynthetically active radiation.

LCDI. 2019. Pemetaan Lahan Gambut Menggunakan Citra Satelit Aktif dan Pasif. *Low Carvon Development Indonesia.* Jakarta

Lymburner L, Beggs PJ, & Jacobson CR. 2000. Estimation of canopy-average surface-specific leaf area using Landsat TM data. *Photogrammetric Engineering and Remote Sensing*, 66(2): 183-192.

Madinu AMA, Jouhary NA, Ulfa A, Rahmadhanti IN, Pudjawati NH, Asy'Ari R, Zamani NP, Pramulya R & Setiawan, Y. 2024. Monitoring of coastal dynamics at Subang Regency using Landsat Collection Data and Cloud Computing Based. *In BIO Web of Conferences,* 106: 1-18. https://doi.org/10.1051/bioconf/202410604005

Mahrad BE, Newton A, Icely JD, Kacimi I, Abalansa S, Snoussi M. 2020. Contribution of remote sensing technologies to a holistic coastal and marine environmental management framework: a review. Remote Sensing, 12(14): 2313. https://doi.org/10.3390/rs12142313

Main-Knorn M, Pflug B, Louis J, Debaecker V, Müller-Wilm U & Gascon F. 2017. Sen2Cor for sentinel-2. I*n Image and signal processing for remote sensing XXIII,* 10427: 37-48. https://doi.org/10.1117/12.2278218

Miller JD, Knapp EE, Key CH, Skinner CN, Isbell CJ, Creasy RM, & Sherlock JW. 2009. Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA.

*Remote Sensing of Environment*, 113(3): 645-656. https://doi.org/10.1016/j.rse.2008.11.009

Miller JD, Thode AE. 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote sensing of Environment*, 109(1): 66-80. https://doi.org/10.1016/j.rse.2006.12.006

Minasny B, Berglund Ö, Connolly J, Hedley C, de Vries F, Gimona A, & Widyatmanti W. 2019. Digital mapping of peatlands–A critical review. *Earth-Science Reviews*, 196: 102870. https://doi.org/10.1016/j.earscirev.2019.05.014

Nasery S & Kalkan K. 2020. Burn area detection and burn severity assessment using Sentinel 2 MSI data: The case of Karabağlar district, İzmir/Turkey. *Turkish Journal of Geosciences*, 1(2):72-77.

Nugraha ES, Madinu AMA, Jannah SZ, Ameiliani TH, Asy'Ari R, Prameswari FA, Zulfajrin M, Nurazizah LL, Putra MCA, Khairunnisa ZN, Rahmawati AD, Setiawan Y, Anggodo A. 2024. Investigating the Impact of the Tsunami at Handeleum Island Resort, Ujung Kulon National Park Using Geospatial Technology. *SSRS Journal B: Spatial Research*, 2, 24-35. https://publishing.ssrs.or.id/ojs/index.php/ssrs-b/article/view/25

Phiri D, Simwanda M Salekin S, Nyirenda VR, Murayama Y & Ranagalage M. 2020. Sentinel-2 data for land cover/use mapping: A review. *Remote Sensing*, 12(14): 1-35. https://doi.org/10.3390/rs12142291

Picotte JJ, & Robertson, K. 2011. Timing constraints on remote sensing of wildland fire burned area in the southeastern US. *Remote Sensing*, 3(8), 1680-1690. https://doi.org/10.3390/rs3081680

Pratama BB, Pratiwi D, & Qirom MA. 2023. Monitoring and identifying forest burnt area using NBR Landsat and Landuse in Central Kalimantan. *IOP Conference Series: Earth and Environmental Science*, 1241(1) 012107. https://doi.org/10.1088/1755-1315/1241/1/012107

Rahmawati AD, Priyanto P & Yovi EY. (2023,). Analysis of OSH risk level in forest management activities using remote sensing approach in RPH Takokak, KPH Sukabumi, West Java Province. *In IOP Conference Series: Earth and Environmental Science*, 1266: 1-16. https://doi.org/10.1088/1755-1315/1266/1/012033

Rizqika SN, Prasetyo Y & Yusuf MA. 2022. Analisis akurasi perbandingan algoritma indeks kebakaran hutan berdasarkan citra sentinel-2A, *Elipsoida*, 5(1):1-7. https://doi.org/10.14710/elipsoida.2022.16858

Roy DP, Boschetti L, Trigg S. N. (2006). Remote sensing of fire severity: assessing the performance of the normalized burn ratio. I*EEE Geoscience and remote sensing letters*, 3(1), 112-116. https://doi.org/10.1109/LGRS.2005.858485

Roy DP, Li Z, Giglio L, Boschetti L & Huang H. 2021. Spectral and diurnal temporal suitability of GOES advanced baseline imager (ABI) reflectance for burned area mapping. *The International Journal of Applied Earth Observation and Geoinformation*, 96:1-14. https://doi.org/10.1016/j.jag.2020.102271

Rowland JA, Bracey C, Moore JL, Cook CN, Bragge P, Walsh JC. 2021. Effectiveness of conservation interventions globally for degraded peatlands in cool-climate regions. *Biological Conservation*, 263: 109327. https://doi.org/10.1016/j.biocon.2021.109327

Saharjo BH. 2023. GHG Emissions' Estimation from Peatland Fires in Indonesia—Review and Importance of Combustion Factor. *Vegetation Fires and Pollution in Asia*, 433-445. https://doi.org/10.1007/978-3-031-29916-2_25

Santos SMBD, Bento-Gonçalves A, Franca-Rocha W & Baptista G. 2020. Assessment of burned forest area severity and postfire regrowth in chapada diamantina national park (Bahia, Brazil) using dnbr and rdnbr spectral indices. *Geosciences*, 10(3):1-19. https://doi.org/10.3390/geosciences10030106

Saputra E, Khaira U & Abidin Z. 2021. Implementasi algoritme SVM untuk klasifikasi area terbakar di lahan gambut. *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, 10(1): 19-24. https://doi.org/10.22146/jnteti.v10i1.990

Saragi-Sasmito MF, Murdiyarso D, June T & Sasmito SD. 2019. Carbon stocks, emissions, and above ground productivity in restored secondary tropical peat swamp forests. *Mitigation and Adaptation Strategies for Global Change*, 24(1):521-533.https://doi.org/10.1007/s11027-018-9793-0

Sari CP, Subiyanto S & Awaluddin M. 2014. Analisis deforestasi hutan di provinsi Jambi menggunakan metode penginderaan jauh (studi kasus Kabupaten Muaro Jambi). *Jurnal Geodesi Undip*, 3(2), 13-27. https://doi.org/10.14710/jgundip.2014.5203

Saputri HR, Asy'Ari R, Abd Malik AM, Dzulfigar A, Marfi KP, Raihan F, Setiawan Y. 2024. Hotspot Distribution Assessment on The Peat Hydrological Unit (PHU) in Riau Province. *SSRS Journal B: Spatial Research*, 2: 44-56. https://publishing.ssrs.or.id/ojs/index.php/ssrs-b/article/view/30

Saputri HR, Inanda IA, Rahmadhanti IN, Asy'Ari R, Fadhil MH, Adni SF, Raihan F, Putra EI, Setiawan Y, Pramulya R, & Zamani NP. 2024B. Data Indo InaPeat: An Environmental Monitoring Platform on Peatlands Area and PHU (Peat Hydrological Units) using Earth Engine Apps. *SSRS Journal A: Agro-Environmental Research*, 2: 20–27. https://publishing.ssrs.or.id/ojs/index.php/ssrs-a/article/view/19

Sutikno S, Rinaldi R, Saputra E, Kusairi M, Saharjo BH, & Putra EI. 2020. Water management for hydrological restoration and fire prevention in tropical peatland. *IOP Conference Series: Materials Science and Engineering*, 933(1): 012053. https://doi.org/10.1088/1757-899X/933/1/012053

Scheip CM & Wegman KW. 2021. HazMapper: a global open-source natural hazard mapping application in Google Earth Engine. *Natural Hazards and Earth System Sciences*, 21(5), 1495-1511. https://doi.org/10.5194/nhess-21-1495-2021

Septian A, Junedi H & Mastur AK. 2023. Estimasi cadangan karbon bawah permukaan lahan gambut di Desa Catur Rahayu Kecamatan Dendang Kabupaten Tanjung Jabung Timur. *Jurnal Tanah dan Sumberdaya Lahan*, 10(2):285-295. https://doi.org/10.21776/ub.jtsl.2023.010.2.12

Sheykhmousa M, Mahdianpari M, Ghanbari H, Mohammadimanesh F, Ghamisi P & Homayouni S. 2020. Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 6308-6325. https://doi.org/10.1109/JSTARS.2020.3026724

Surahman A, Shivakoti GP, & Soni P. (2019. Climate change mitigation through sustainable degraded peatlands management in central Kalimantan, Indonesia. *International Journal of the Commons*, 13(2): 859-866. https://www.jstor.org/stable/26819573

Syaufina L, Sitanggang IS, Anggraini A & Afina FS. 2021. Fire severity assessment on peatland vegetation diversity. I*OP Conference Series: Earth and Environmental Science,* 1025: 1-10. https://doi.org/10.1088/1755-1315/1025/1/012014

Rad AM, Kreitler J, & Sadegh, M. 2021. Augmented Normalized Difference Water Index for improved surface water monitoring. *Environmental Modelling & Software*, 140: 105030. https://doi.org/10.1016/j.envsoft.2021.105030

Ranti A, Asy'Ari R & Ameiliani TH. 2022. Detection of Urban Forest Change in Jabodetabek Megacity Using Sentinel 2 and Landsat 8 Imagery Through Google Earth Engine Cloud Computing Platform. *In IOP Conference Series: Earth and Environmental Science,* 959(1): 012028. https://iopscience.iop.org/article/10.1088/1755-1315/959/1/012028

Teodoro A & Ana A. 2019. A statistical and spatial analysis of portuguese forest fires in summer 2016 considering landsat 8 and sentinel 2A data. *Environments*, 6(3):36-50. https://doi.org/10.1088/1755-1315/1025/1/01201

Xu H. 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14): 3025-3033. https://doi.org/10.1080/01431160600589179

Xu H. 2008. A new index for delineating built-up land features in satellite imagery. *International Journal of Remote Sensing*,29(14): 4269-4276. https://doi.org/10.1080/01431160802039957

Xiao X, Boles S, Frolking S, Salas W, Moore Iii B, Li C, Zhao R. 2002. Observation of flooding and rice transplanting of paddy rice fields at the site to landscape scales in China using VEGETATION sensor data. *International Journal of Remote Sensing*, 23(15): 3009-3022. https://doi.org/10.1080/01431160110107734

Vedovato LB, jacon AD, Pessôa ACM, Lima A, Oliveira LE & De Aragão CRUZ. 2015. Detection of burned forests in Amazonia using the normalized burn ratio (NBR) and linear spectral mixture model from Landsat 8 images. *Anais XVII Simpósio Brasileiro de Sensoriamento Remoto (SBSR)*. 25:2984-2991

Ward SE, Bardgett RD, McNamara NP, Adamson JK, Ostle NJ. 2007. Long-term consequences of grazing and burning on northern peatland carbon dynamics. *Ecosystems* 10: 1069-1083. https://doi.org/10.1007/s10021-007-9080-5

Weng Q. 2009. Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. *ISPRS Journal of photogrammetry and remote sensing*, 64(4), 335-344. https://doi.org/10.1016/j.isprsjprs.2009.03.007

Widodo RB. 2014. Pemodelan spasial resiko kebakaran hutan (studi kasus Provinsi Jambi, Sumatera). *Jurnal Pembangunan Wilayah & Kota*, 10(2): 127-138. https://doi.org/10.14710/pwk.v10i2.7643

Zhang C, Di L, Yang Z, Lin L & Hao P. 2020. AgKit4EE: A toolkit for agricultural land use modeling of the conterminous US based on google earth engine. *Environmental Modelling & Software*, 129: 1-33. https://doi.org/10.1016/j.envsoft.2020.104694

Zhao S, Liu M, Tao M, Zhou W, Lu X, Xiong Y, Wang Q. 2023. The role of satellite remote sensing in mitigating and adapting to global climate change. *Science of the Total Environment,*904(15): 166820. https://doi.org/10.1016/j.scitotenv.2023.166820