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# Assessment of Peatland Fire Susceptibility Using Biogeophysical Parameters in the Kahayan-Sebangau Peat Hydrological Unit, Central Kalimantan

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**Abstract:** Forest and land fires in peatland ecosystems of Central Kalimantan pose a serious threat to the environment and local communities, causing ecosystem degradation, loss of biodiversity, and health problems. This study aims to identify biophysical characteristics, analyze the relationships between environmental parameters and fire occurrences, and develop a vulnerability map based on the integration of remote sensing data and spatial modeling. Multisource data (Sentinel-2, Landsat-8, MODIS, CHIRPS, ERA5-Land, and TerraClimate) were used to obtain 15 variables representing topography, hydrology, vegetation, and climate, which were further analyzed to detect burned areas using the differenced Normalized Burn Ratio (dNBR). The dataset was divided into 70% for training and 30% for validation. Fire vulnerability mapping using the Random Forest Probability (RFP) method resulted in six risk classes: very low (143,994 ha), low (104,909 ha), moderate (85,718 ha), high (58,541 ha), very high (40,597 ha), and extreme (16,230 ha). The model demonstrated strong performance with an AUC value > 0.85, indicating consistent relationships between classification results and key environmental variables, where land surface temperature (LST), rainfall, and vegetation indices (NDVI and NDMI) were identified as the most influential factors affecting fire vulnerability. The findings provide recommendations for ecosystem-based peatland restoration, adaptive peat management, and fire mitigation strategies within the Kahayan–Sebangau PHU landscape.

**Keyword:** Peatland fire, random forest probability, remote sensing

## INTRODUCTION

Peatlands are one of the most ecologically important wetland ecosystems due to their ability to store large amounts of carbon, despite covering only 4 million km² (3% of the world's total land area) (Freeman *et al.* 2022; Austin *et al.* 2025). According to Loisel dan Sala (2022), peatlands contain an estimated 25–33% of the global carbon stock. Peatlands are found in more than 170 countries and cover approximately 3-4% of the world's land area, yet they store up to one-third of the total global soil carbon, making them one of the largest carbon storage ecosystems on Earth (UNEP 2022). Indonesia is the largest tropical peatland center, with a total area of approximately 13.43 million ha, where Kalimantan ranks second after Sumatra with a peatland area of approximately 4.54 million ha or nearly one-third of the national total (KLHK 2022; Ribeiro *et al.* 2021). Peatlands in this region are connected through the PHU (Peat Hydrological Unit) or PHU (Peatland Hydrological Unit) system. A PHU serves as a peatland ecosystem management unit formally established by the Indonesian government to maintain the ecological and hydrological sustainability of peat ecosystems.

According to Government Regulation of the Republic of Indonesia Number 71/2014, peatland is defined as an organic material naturally formed from partially decomposed vegetation that accumulates under water-saturated conditions in swamp areas over thousands of years. This accumulation process generally occurs in backswamps, which are associated with the natural levees of the rivers that flank them (Maas *et al.* 2020). PHU management is based on the principle of a peat dome-based water balance, in which water balance is a key factor in maintaining the hydrological and ecological functions of peat ecosystems (Apers *et al.* 2022). A single PHU unit may consist of one or more peat domes, each with a distinct hydrological system. The morphological profile of tropical peat domes is divided into a relatively flat and flooded zone (dome peak), a steeper gradient slope (dome slope), and a transitional zone between the dome and the surrounding ecosystem (dome foot). Fiantis *et al.* (2023) reported a strong correlation between peat surface elevation and peat thickness, with the thickest layers generally occurring at the dome summit. This supports the concept of a dome, where the summit zone tends to be higher and flooded and differs from the foot zone in terms of thickness and carbon potential. In some instances, several domes may share the same dome foot, but have different slopes and peaks. Peaks with separate hydrological systems within a single PHU are called sub-PHUs. This water balance-based management approach has important implications for carbon conservation, climate change mitigation, and peat fire prevention. Hydrological imbalances, such as a decline in groundwater levels due to excessive drainage, can lead to peat oxidation (mineralization), significant carbon release in the form of CO2, and increased susceptibility to fires (Ma *et al.* 2022). Research conducted by Fawzi *et al.* (2024) also explains that drainage can significantly increase $CO_2$ and $N_2O$ emissions through oxidative decomposition processes in peatlands that have been burned or whose hydrological cycles have been disrupted. Therefore, accurate mapping of PHU and sub-PHUs is a crucial first step toward effective peatland ecosystem restoration planning.

Kahayan–Sebangau PHU in Central Kalimantan is one of the peatland landscapes with high conservation value and vital hydrological and ecological functions, including as a habitat for key species such as the Bornean orangutan (*Pongo pygmaeus* ssp. wurmbii) and various other endemic flora and fauna (Panda dan Kasih 2020). However, this area is also one of the regions most affected by recurrent peat fires in the last two decades (Ramadhani *et al.* 2023). The fires that occur in this PHU not only cause damage to surface ecosystems but also affect biogeophysical dynamics such as changes in land cover, decreased soil water content, vegetation degradation, and disruption to microclimate stability. Forest and peatland fires in Kalimantan are primarily caused by human activities related to deforestation, land use change, and the preparation of agricultural commodities by burning land (Rezainy *et al.* 2020). Despite various mitigation and restoration efforts, there are still limitations in scientific understanding of how fires affect biogeophysical dynamics spatially and temporally within PHU. Most previous studies have been local and temporary in nature, and therefore have not been able to describe the dynamics of ecosystem change comprehensively. Therefore, approaches based on remote sensing data, spatial modeling, and the integration of multi-source data such as land cover, hotspots, vegetation indices, and hydrometeorological parameters are essential for identifying the impacts of fires more comprehensively.

Ecosystem degradation and changes in biogeophysical conditions within the Kahayan–Sebangau PHU have increased vulnerability to fires, highlighting the need for a comprehensive study on the relationship between biogeophysical factors and fire occurrences. Remote sensing and spatial modeling approaches provide an opportunity to analyze environmental dynamics both temporally and spatially across a broad area. The integration of multisource satellite data with 15 biogeophysical variables in this study represents a novel approach capable of depicting peatland fire susceptibility in greater detail and accuracy compared to previous studies. Therefore, this research aims to identify the biogeophysical characteristics of the Kahayan–Sebangau PHU, including topographic, vegetation, and meteorological factors; to analyze the relationships between biogeophysical parameters and peatland fire occurrences; and to develop a fire vulnerability map based on biogeophysical factors through the integration of remote sensing data and spatial modeling. The findings of this study are expected to provide a scientific basis for ecosystem-based restoration planning, adaptive peatland management, and fire mitigation strategies within landscape level priority areas.

## METHODOLOGY

### Study Area

Geographically, the Kahayan–Sebangau PHU is situated in Central Kalimantan Province, encompassing parts of the administrative areas of Palangka Raya City, Pulang Pisau Regency, and Katingan Regency. Astronomically, this PHU is located between approximately 1°30'–3°00' south latitude and 113°30'–114°30' east longitude Fig. 1. The study area is located within a tropical climate zone characterized by a bimodal rainfall pattern, with two distinct rainy seasons typically occurring in April–May and December–January (Saharjo dan Hasanah 2023). According to Sukarna (2008) the peat swamp forests in this region are classified as Type A under the Schmidt–Ferguson climate classification, with a Q value of 13.32% and an average monthly rainfall of approximately 173.96 mm. Climate Type A represents a very wet zone, where high precipitation is distributed throughout most of the year. Osaki *et al.* (2016) reported that about 43% of Kalimantan is located within Zone A, which experiences a rainy season lasting more than nine months and a dry season of less than two months. However, some peatland areas are classified within Zone C, which has a rainy season of 5–6 months followed by a dry season lasting 2–3 months.

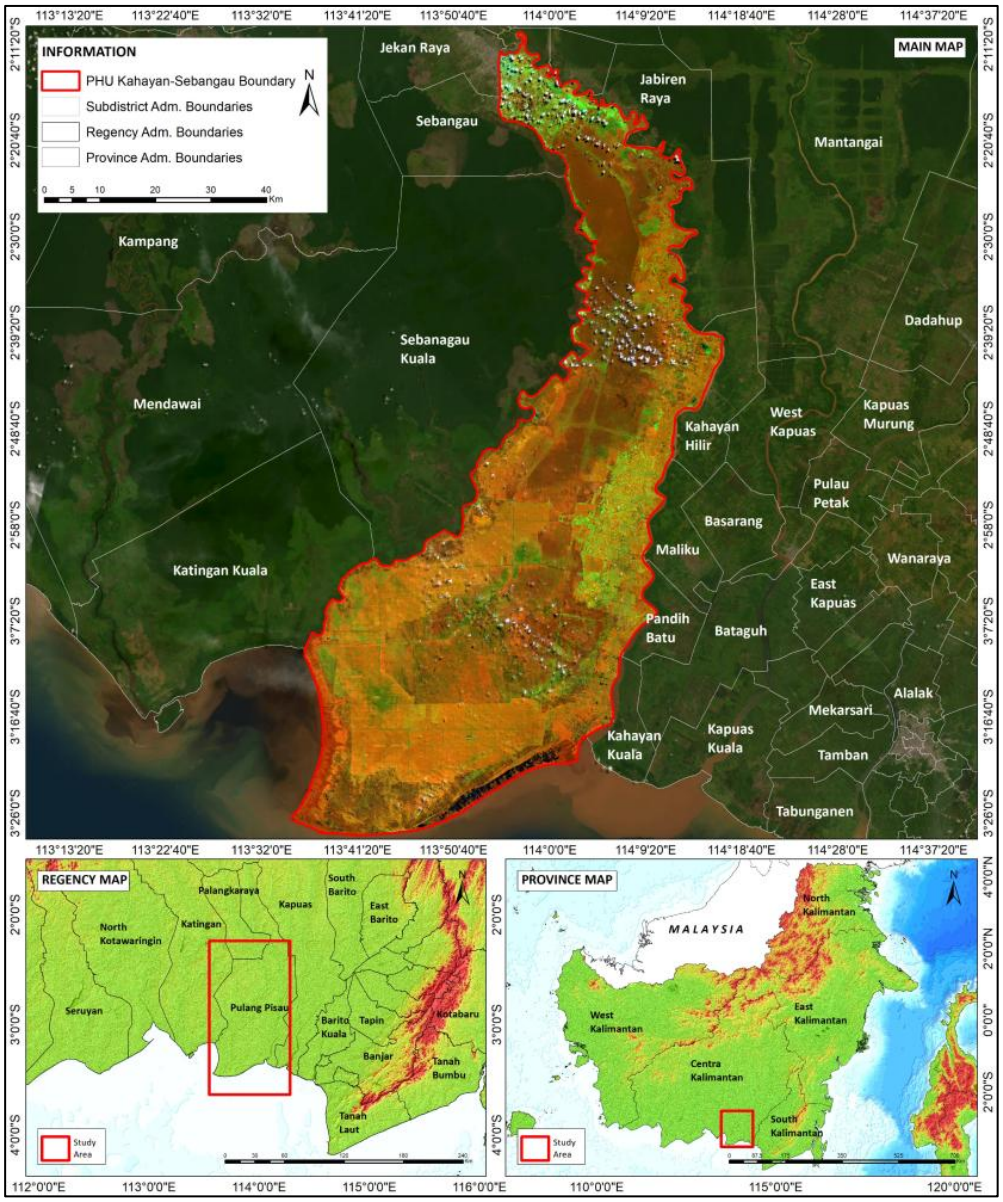



**Figure 1.** Research location

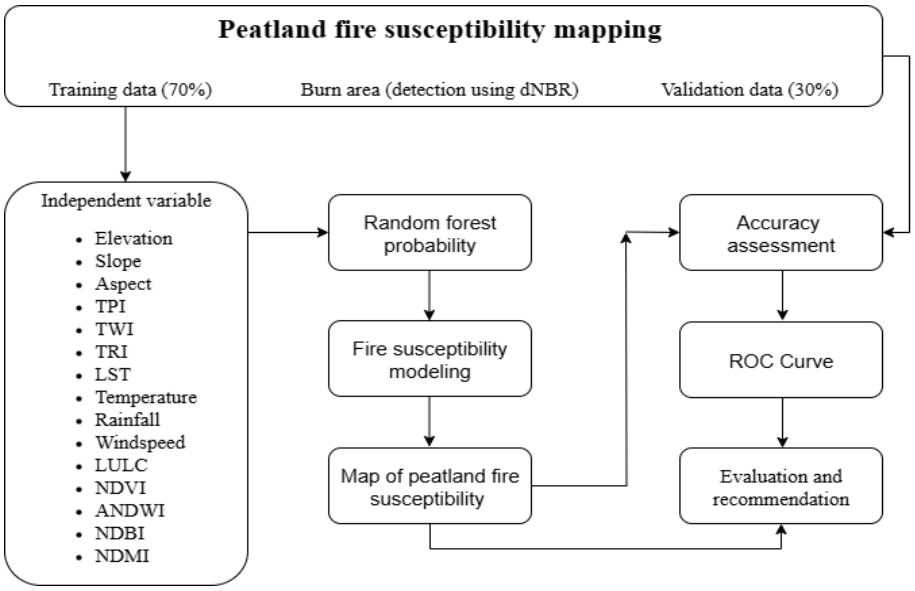



**Figure 2.** Research flow chart

**Table 1.** Dataset sources (independent and dependent variables

| Category | Data Layer | Data Source | Data Type |
|---|---|---|---|
| Dependent | Burn Area (detection using Dnbr) | Landsat-8 OLI/TIRS | Raster |
| Independent | Elevation | DEM SRTM | Raster |
| | Slope | | |
| | Aspect | | |
| | TPI | | |
| | TWI | | |
| | TRI | | |
| | LST | MODIS | Raster |
| | Temperature | ERA5-Land | Raster |
| | Rainfall | CHIRPS | Raster |
| | Windspeed | Terra Climate | Raster |
| | LULC | Landsat-8 OLI/TIRS | Raster |
| | NDVI | | |
| | ANDWI | | |
| | NDBI | | |

## Data Source and Resources

This study employed Sentinel-2 Multispectral Instrument (MSI) imagery acquired from the United States Geological Survey (USGS) and processed using the Google Earth Engine (GEE) platform. Administrative boundary data were obtained from the Badan Informasi Geospasial (BIG). Concurrently, the boundaries for the Kahayan–Sebangau Peatland Hydrological Unit (PHU) were sourced from the Badan Restorasi Gambut dan Mangrove (BRGM). The complete research workflow is illustrated in Fig. 2.

## Fire Ignition Factors

Forest and land fire vulnerability, particularly within the Peatland Hydrological Unit (PHU) region, can be defined as the probability of fire occurrence in a given area (Bui *et al.* 2018). This vulnerability is contingent upon several predisposing factors. To generate the fire vulnerability map for our study area, 15 relevant biophysical factors, including environmental variables, were utilized as the primary data influencing fire occurrence. The biophysical factors influencing an area's fire vulnerability are categorized into three main groups: topographic, meteorological, and vegetation. The topographic factors employed in this study included elevation, slope, aspect, Topographic Wetness Index (TWI), Topographic Ruggedness Index (TRI), and Topographic Position Index (TPI). Meteorological factors comprised rainfall, relative humidity (RH), wind

speed, temperature, and land surface temperature (LST). Vegetation factors encompassed the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), and Normalized Difference Moisture Index (NDMI). Generally, image-based indices such as NDVI, NDBI, NDWI, and the Automated Non-Land Water Index (ANDWI) are classified as land cover factors, often aggregated with vegetation. However, the NDMI is more appropriately categorized as a vegetation factor in this context, as it specifically indicates vegetation moisture. Overall factor importance was assessed using two indicators, Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG), to quantify the importance of each variable to the model (Deng *et al.* 2018). MDA quantifies the extent to which model accuracy declines when a variable's values are permuted, while MDG represents the variable's contribution to node splitting within the decision trees (Halstead *et al.* 2025).

## Peatland Fire Susceptibility Mapping Using Random Forest Probability

Vulnerability mapping for forest and land fires was conducted using a Random Forest Probability (RFP) approach. The model employed a training dataset consisting of independent variables (predictors) and a dependent variable (response) Table 1. The dependent variable, fire occurrence, was derived from the dNBR

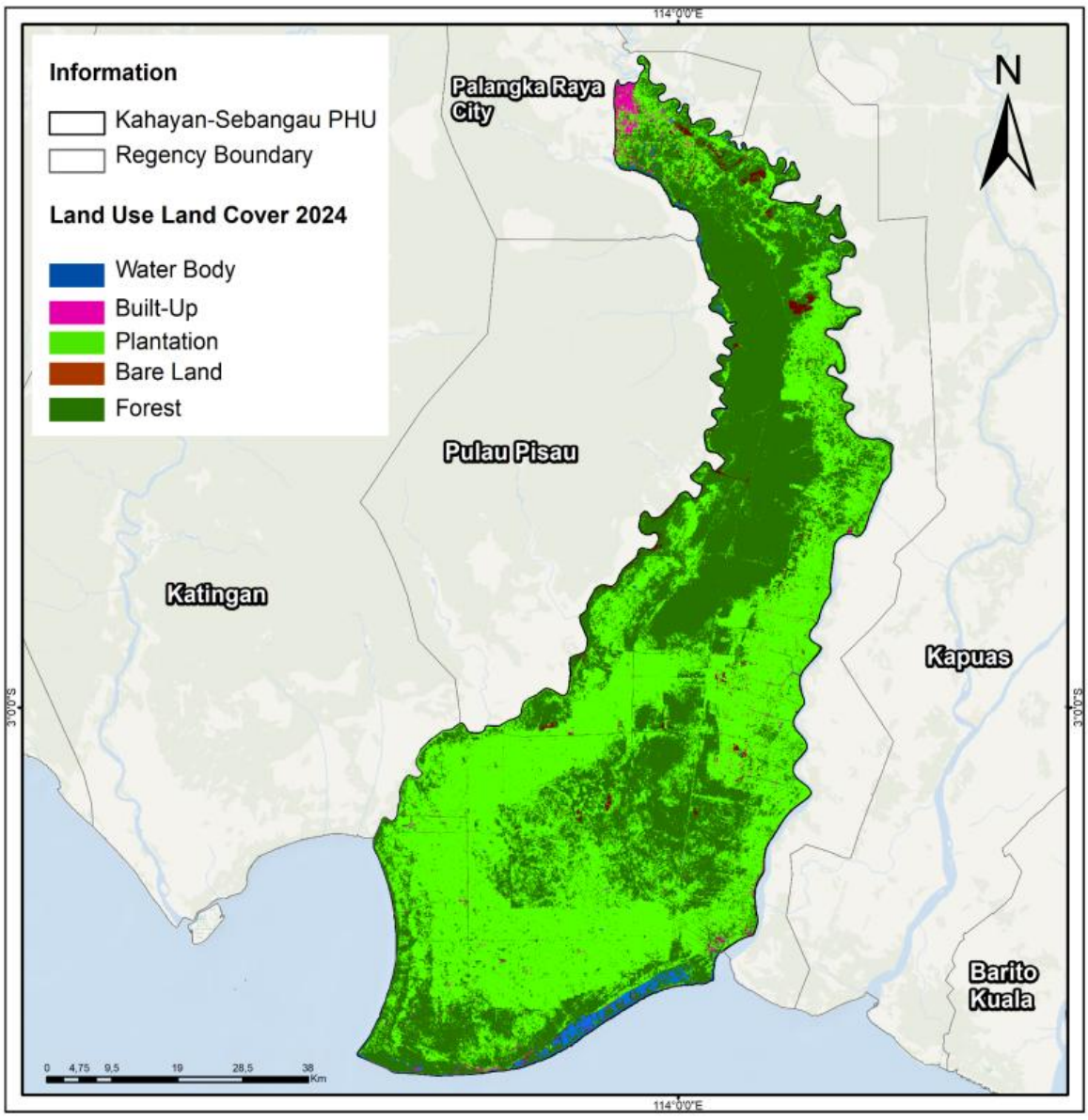



**Figure 3.** LULC change in 2024

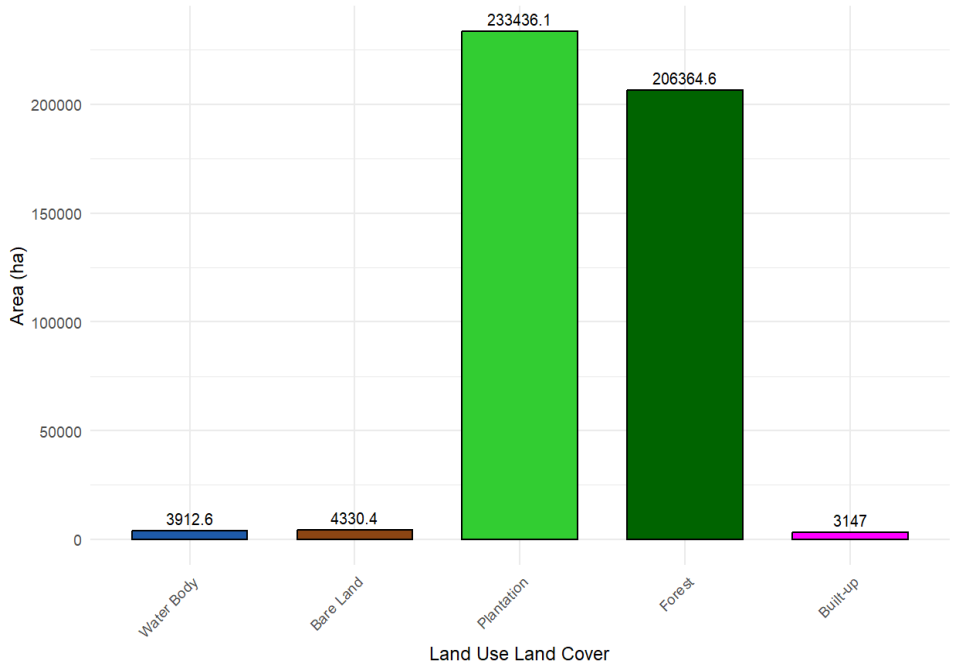



**Figure 4.** LULC aera in 2024

index, which is calculated based on pre- and post-fire spectral reflectance (Ghazali *et al.* 2025). Pre-processing steps included atmospheric correction, cloud masking, resampling to a 30 m resolution, and clipping to the study boundary. A threshold-based dNBR classification was applied to distinguish burned from unburned areas, with the resulting categories calibrated against standard post-fire severity thresholds. The training and validation dataset comprised 2,000 total points, categorized as burned and unburned. This dataset was randomly partitioned into 70% for training and 30% for validation to ensure model reliability and prevent overfitting.

Random Forest (RF), an ensemble learning algorithm (Xu *et al.* 2019), is widely adopted in environmental science for its robustness in managing non-linear relationships, multicollinearity, and complex datasets. The Random Forest Probability (RFP) approach leverages RF regression to estimate the probability of fire occurrence, yielding an output value ranging from 0 to 1. This probability-based method enables the classification of regions according to their fire vulnerability levels. The model was constructed using 15 predictor variables Fig. 3 and Fig. 7 comprising biophysical, meteorological, and anthropogenic factors known to influence fire events.

### Performance Assessment

The performance of the forest fire susceptibility model was assessed using the Receiver Operating Characteristic (ROC) curve and the Area the Curve (AUC). Bui *et al.* (2018) explained that the ROC curve is a descriptive graph constructed based on sensitivity versus specificity. The modal is considered perfect if an AUC value of 1 is obtained, whereas the modal is uninformative if the AUC yields a value of 0. An AUC value approaching 0.5 indicates poor model performance (Huang dan Liu 2025).

## RESULTS AND DISCUSSION

### Land Use Land Cover Change

The 2024 Land Use-Land Cover (LULC) analysis of the Kahayan–Sebangau PHU revealed a dominance of two primary classes: plantations and forest. Plantations accounted for 233.436 ha, while forests covered 206.364 ha. Other cover types comprised a significantly smaller proportion, namely water bodies (3.912 ha), open land (4.330 ha), and built-up land (3.147 ha) Fig. 4. Spatially, forests were predominantly distributed across the central and southern parts of the area, whereas plantations were concentrated in the northern region and in zones adjacent to settlements Fig. 3.

The dominance of plantations in this area is inextricably linked to the post-2000 expansion of oil palm, which was driven by governmental policy shifts during the post-reform era (late 1990s) that relaxed

regulations on investment and land tenure, favoring corporations (Ayu 2021). This trend was further exacerbated by high global demand for vegetable oil as a foodstuff, cosmetic, and energy source (Syahril *et al.* 2022). Central Kalimantan's peat landscapes became a major epicenter for this expansion, owing to extensive land availability and government policies granting large-scale concessions (Dohong *et al.* 2018). Ayu (2021) reported that the Central Kalimantan government initially allocated approximately four million hectares for plantations; consequently, 23.45 percent of this area was already under oil palm cultivation. This forest-to-plantation conversion ultimately led to severe ecosystem degradation, increased fire risk, and the release of substantial carbon emissions (Mishra *et al.* 2021). Nevertheless, the 2024 mapping results indicate that the extent of forest cover in the Kahayan–Sebangau PHU remains relatively large, signifying a potential for peat ecosystem recovery. This aligns with the implementation of the national peat restoration program following the major 2015 fires, which employs the 3R strategy (Rewetting, Revegetation, and Revitalization) to promote the rehabilitation of critical lands (Puspitaloka *et al.* 2021). The decrease in open and built-up land suggests effective control over non-forest expansion, achieved either through natural revegetation or development control policies in vulnerable zones (Tacconi dab Muttaqin 2019). Meanwhile, the fluctuation in water bodies, reaching nearly 4,000 ha, can be attributed to the recovery of peat hydrological functions resulting from canal blocking and water conservation efforts. These hydrological improvements play a critical role in mitigating fire risk and maintaining the area's hydrological regime (Sutikno *et al.* 2023). The LULC 2024 condition in the Kahayan–Sebangau PHU reflects the dynamic interplay between anthropogenic pressures, primarily plantation expansion, and ecosystem recovery processes driven by restoration policy interventions.

## Spatial Planning Characteristics of the Kahayan-Sebangau PHU

Spatial allocation in the Kahayan-Sebangau PHU is predominantly characterized by forest areas, reflecting a regional spatial planning orientation that prioritizes the maintenance of forest protection and production functions. Protected Forest constitutes the largest category, covering approximately 155,834.39 ha, followed by Permanent Production Forest with an area of 139,401.87 ha. The dominance of these two categories indicates that the spatial structure of the region is directed toward peatland ecosystem protection, hydrological regulation, and the sustainable utilization of forest resources, as emphasized in tropical peatland landscape planning (Page *et al.* 2011; Miettinen *et al.* 2016). The presence of conservation areas, including Nature Reserve covering 6,944.53 ha and National Park covering 2,875.80 ha, further underscores the role of this region as a high conservation value landscape within an ecosystem-based spatial management framework (Gaveau *et al.* 2014). Outside the forest areas, spatial utilization for cultivation and settlement activities is relatively limited. Plantation area, covering approximately 33,528.07 ha, function as non-forest production spaces that support land-based economic activities, while built-up area totaling 22,579.65 ha reflect the concentration of settlements and infrastructure in specific locations. Convertible Production Forest, with a relatively small area of approximately 1,034.40 ha, indicates that the potential for land-use conversion is tightly controlled within the regional spatial structure. This pattern is consistent with land-use planning principles that emphasize a balance between conservation and development functions to reduce environmental degradation (Lambin *et al.* 2014; Foley *et al.* 2005). Overall, the spatial pattern of the Kahayan–Sebangau PHU demonstrates an integrated and controlled arrangement of protection, production, and cultivation functions. Land Use/Land Cover (LULC) maps and fire susceptibility maps serve as supporting tools to illustrate the consistency between spatial allocation and land-use patterns, as commonly applied in spatial planning and landscape management studies (Verburg *et al.* 2011).

## The Relationship Between Environmental Parameters (Biogeophysical Factors) and Fire Susceptibility

The parameters utilized in this analysis are interconnected, mutually influential, and collectively define the fire vulnerability factors in the Kahayan-Sebangau Peat Hydrological Unit (PHU). Topography is one of the primary factors influencing fire susceptibility (Van dan Lee 2025). The topographic parameters, including elevation, slope, aspect, Topographic Wetness Index (TWI), Topographic Ruggedness Index (TRI), and Topographic Position Index (TPI), play an essential role in determining fire-prone areas. Low-elevation areas, such as those found in the Kahayan–Sebangau PHU, generally accumulate fuel in the form of dry litter, especially during the dry season. This litter is derived from vegetation such as

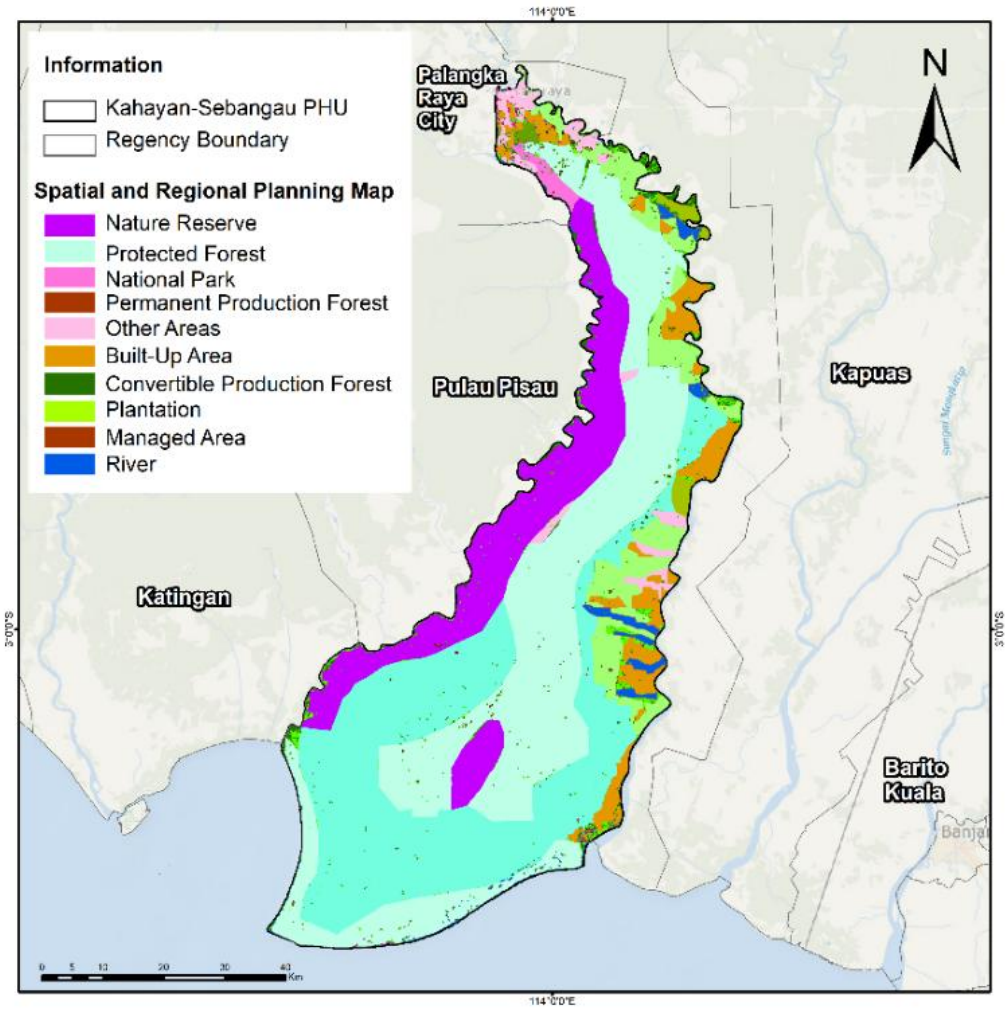



**Figure 5.** Spatial and regional planning map in Kahayan-Sebangau PHU

shrubs, leaves, twigs, branches, and ferns that have dried out. Low-lying areas also tend to have higher temperatures compared to higher elevations, making them more susceptible to fire ignition when sufficient fuel is available (Eskandari *et al.* 2020). Slope is another parameter that significantly influences fire susceptibility. Steep slopes are generally prone to rapid upslope fire spread from valleys to ridges. However, unique conditions exist in the Kahayan–Sebangau PHU, where gentle to flat slopes are also highly susceptible to fires. Flat terrain facilitates horizontal fire movement and rapid spread, particularly in peatlands, which are prone to both surface and subsurface (underground) fires. Flat areas allow for uniform accumulation and distribution of organic fuel and lack significant topographic barriers that could limit fire spread. Furthermore, the combination of aspect, TWI, TRI, and TPI contributes to the overall fire susceptibility (Mofokeng *et al.* 2024). Aspect influences the amount of solar radiation received by the land surface; areas exposed to direct sunlight tend to dry out surface fuels more quickly. The TWI represents the surface soil moisture content of an area. In natural peat

**Table 2.** Fire susceptibility class

| Number | Area (ha) | Class |
|---|---|---|
| 1 | 143,994 | Very Low |
| 2 | 104,909 | Low |
| 3 | 85,718 | Medium |
| 4 | 58,541 | High |
| 5 | 40,597 | Very High |
| 6 | 16,230 | Extremely High |

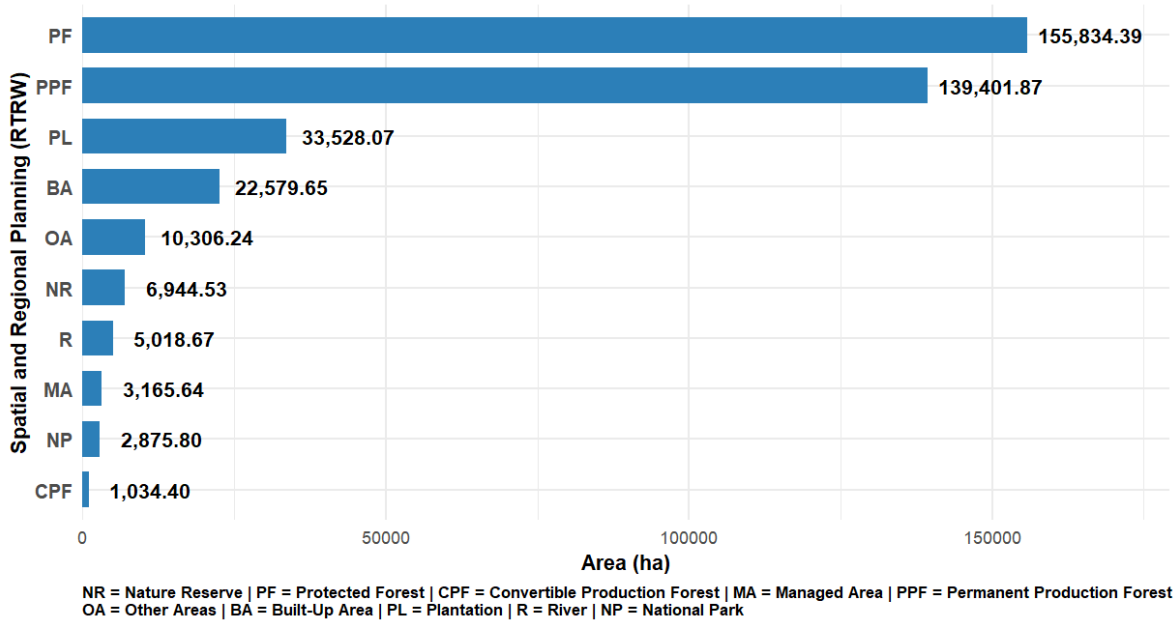



**Figure 6.** Spatial and regional planning area (ha) in Kahayan-Sebangau PHU

ecosystems, TWI values are generally high, indicating stable and moist conditions. However, in the Kahayan–Sebangau PHU, several areas have undergone land conversion and drainage, disrupting peat stability and leading to lower to moderate TWI values. The TRI reflects the heterogeneity of topography, where areas with low TRI values tend to have a consistent availability of fuel. Lastly, the TPI is associated with fuel drying processes across the landscape. Overall, the combined influence of these seven topographic parameters strongly contributes to the fire susceptibility of the Kahayan–Sebangau PHU.

The second parameter is meteorology, which plays a dominant role in influencing fire susceptibility. Low rainfall and decreased relative humidity (RH) reduce vegetation moisture content while increasing air temperature and land surface temperature (LST). This condition is further exacerbated by high wind speeds, which not only accelerate the drying process but also enhance the horizontal spread of fire across flat peatland areas. Therefore, the combination of low rainfall, low RH, high surface temperature, and strong winds serves as the primary determinant of increased fire susceptibility in the Kahayan–Sebangau PHU. The third parameter is vegetation, which is derived from vegetation and land cover indices. Vegetation factors play a crucial role in determining fire susceptibility, as they are directly related to fuel conditions and vegetation moisture content. The analysis of image-based indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), and Automated Non-Land Water Index (ANDWI) revealed spatial variations in land cover and vegetation moisture across the Kahayan–Sebangau PHU. Low NDVI and NDMI values indicate dry vegetation, while high ANDWI and NDBI values represent dominant non-water and open surface areas that tend to absorb more heat. Conversely, low NDWI values suggest limited surface water availability. The combined interpretation of these five indices provides a synergistic understanding of areas most prone to fire, characterized by sparse vegetation, low moisture, and high surface heat exposure. The integration of topographic, meteorological, and vegetation-based parameters enables the development of a reliable model for assessing fire susceptibility in the Kahayan-Sebangau PHU, allowing for more efficient and comprehensive peatland fire risk evaluation.

## Variable Importance and Accuracy

Understanding the variables that contribute significantly to a prediction model is critical for enhancing the accuracy and interpretability of machine learning-based analyses. This study employed 15 biophysical variables Fig. 8 which, as detailed in the methodology, were classified into three primary groups:

topographic, meteorological, and vegetation factors index.

The evaluation results presented in Fig. 8 show that the variables contributing most significantly, or having the highest importance in both Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG), are meteorological factors particularly the Land Surface Temperature (LST). LST represents the temperature of the Earth's surface as measured by satellite sensors (Li *et al.* 2023). This variable indicates that surface temperature serves as a primary indicator of fuel dryness. High surface temperatures increase the rate of soil and vegetation moisture evaporation, thereby elevating the risk of fire occurrence (Adeyeri *et al.* 2024). Other meteorological variables, such as wind speed and rainfall, rank fourth and fifth in importance in influencing fire susceptibility within the Kahayan–Sebangau PHU. Rainfall plays a crucial role in maintaining fuel moisture availability, where prolonged low precipitation contributes to vegetation desiccation, increasing its flammability (Diószegi *et al.* 2023). Wind speed is a critical factor that accelerates fire spread, as it not only supplies oxygen for combustion but also carries embers to new areas, expanding the fire front (Liu *et al.* 2021). The formation of fire is governed by three primary elements: oxygen, fuel, and heat. When these components coexist, ignition is more likely to occur, particularly in highly susceptible regions. In

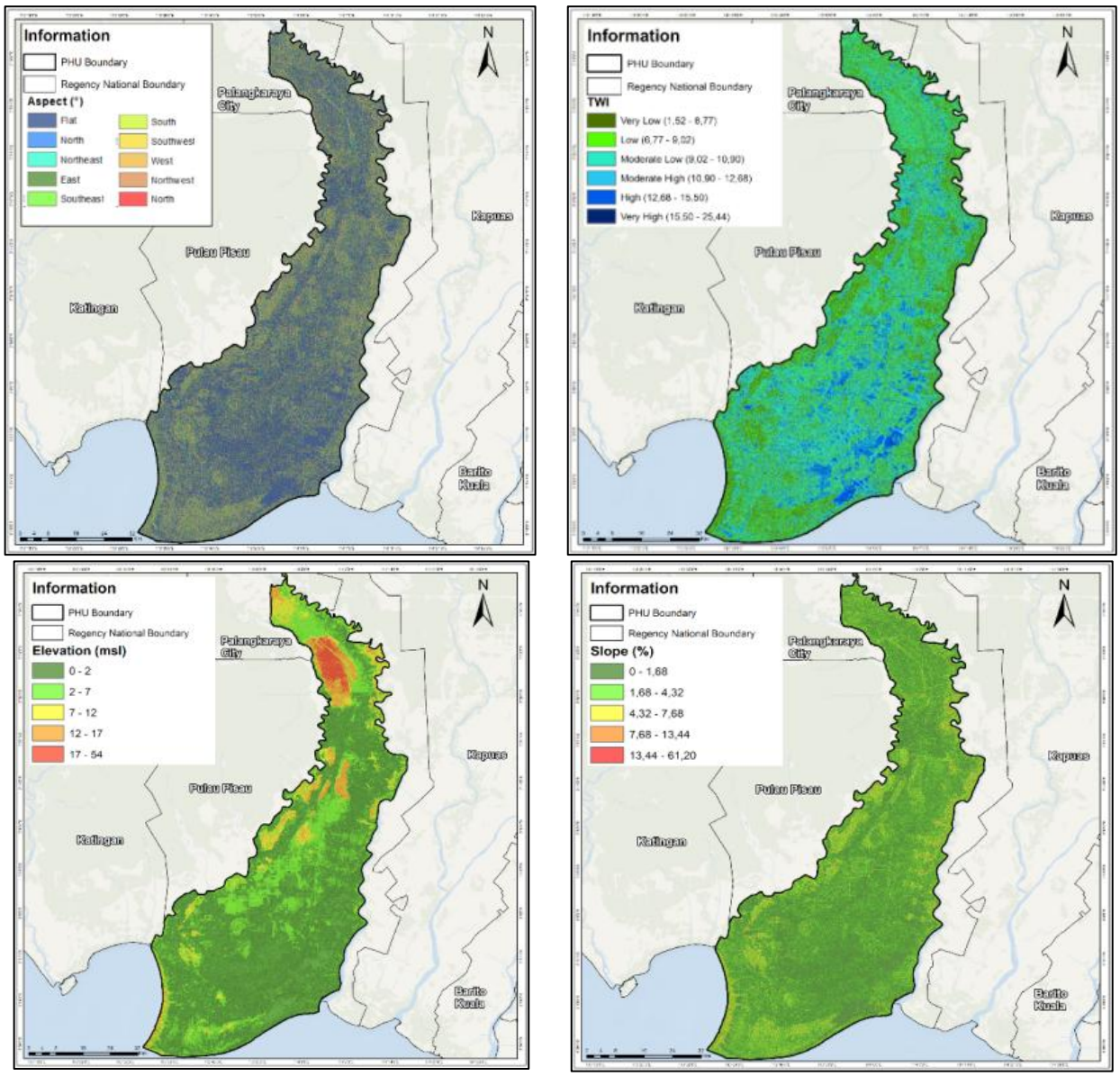



**Figure 7.** Forest fire variables (Topographic: Elevation, slope, aspect, TWI, TRI, and TPI; Meteorology: Rainfall, Wind speed, Temperature, and LST; Vegetation index: NDVI, NDMI, ANDWI, and NDBI)

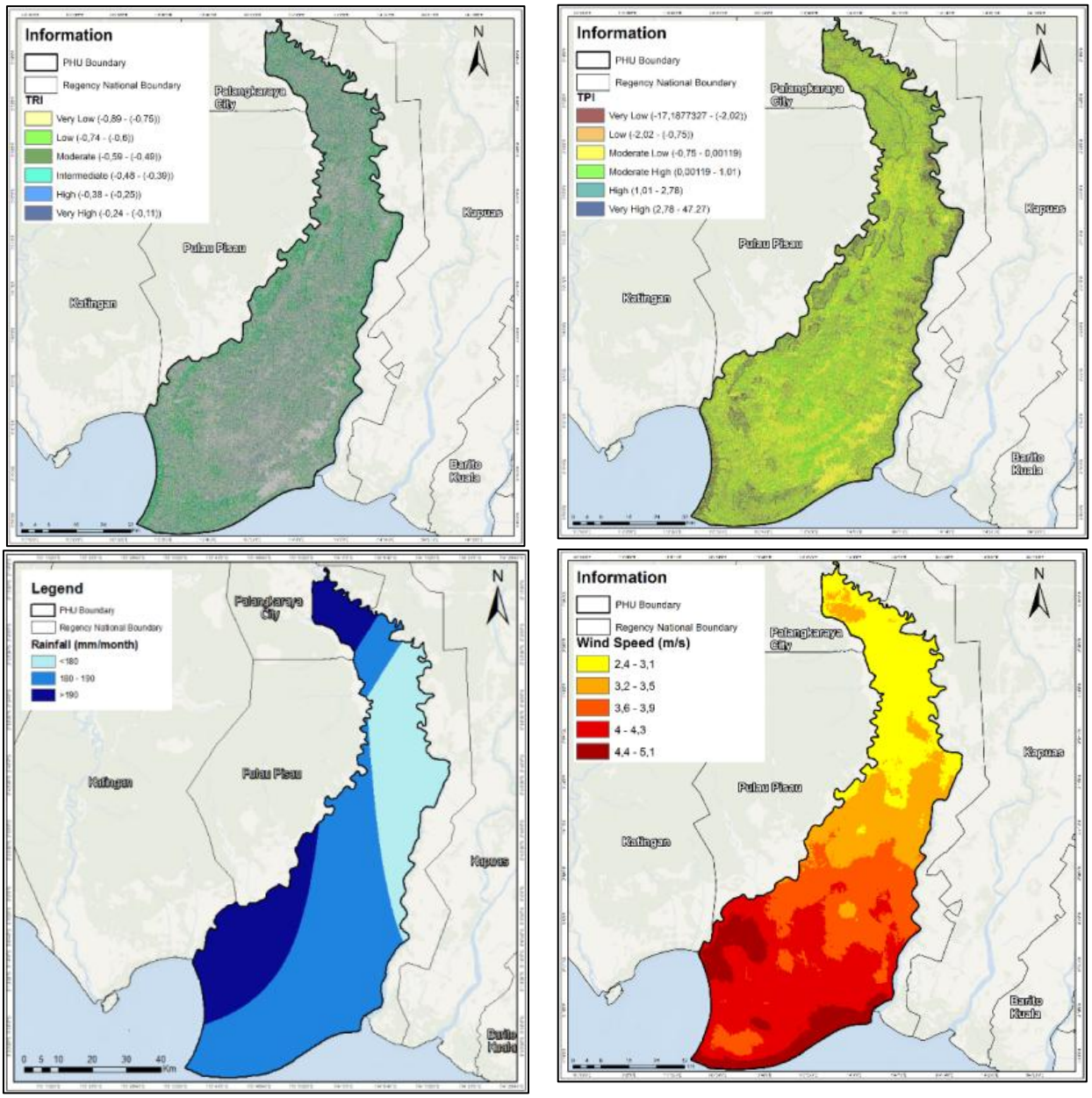



**Figure 7.** Forest fire variables (Topographic: Elevation, slope, aspect, TWI, TRI, and TPI; Meteorology: Rainfall, Wind speed, Temperature, and LST; Vegetation index: NDVI, NDMI, ANDWI, and NDBI) (Continue)

addition to meteorological factors, image-based vegetation indices also demonstrate significant contributions. The Normalized Difference Moisture Index (NDMI) serves as an indicator of vegetation moisture, where lower NDMI values reflect drier vegetation and higher fire susceptibility (Ahmad *et al.* 2025). Meanwhile, the Normalized Difference Built-up Index (NDBI), commonly used to identify built-up areas, also plays an important role, as regions experiencing anthropogenic pressure tend to exhibit increased fire frequency (Kolanek *et al.* 2021). Other vegetation indices, such as the NDVI and NDWI, although contributing less than NDMI, remain relevant indicators of vegetation and surface moisture availability that influence fire dynamics. Conversely, topographic variables such as slope, aspect, and land use-land cover (LULC) show relatively lower contributions to the model. This finding aligns with previous studies, which suggest that meteorological factors directly influence fuel conditions and fire initiation, whereas topographic factors primarily control fire propagation patterns once ignition has occurred (Zahura *et al.* 2024; Cardoso *et al.* 2025). Therefore, the findings of this study reaffirm that while all biogeophysical factors contribute to fire susceptibility, meteorological conditions and vegetation moisture

serve as the principal determinants in predicting the vulnerability of a region to forest fires (*Karurung et al.* 2025; Choi *et al.* 2024).

The classification of fire susceptibility in the study area was evaluated using the Receiver Operating Characteristic (ROC) curve. The performance of the Random Forest model in predicting forest fire susceptibility levels was assessed based on the Area Under the Curve (AUC) value. The ROC curve illustrates the relationship between the True Positive Rate (TPR) or sensitivity on the y-axis and the False Positive Rate (FPR) or 1-specificity on the x-axis. Each point on the curve represents a combination of TPR and FPR for different classification thresholds. Accordingly, the ROC curve can also be used to determine the optimal cut-off or threshold value. An AUC value of 0.888 indicates that the model has an excellent classification ability to distinguish between fire-prone and non-fire-prone areas. The classification accuracy of 80% further confirms the moSdel's effective performance, as shown in Fig. 9. The closer the AUC value is to 1, the higher the model's predictive accuracy. These findings are consistent with those reported by Lee *et al.* (2025), who demonstrated that machine learning–based methods such as Random Forest consistently yield accurate results in modeling

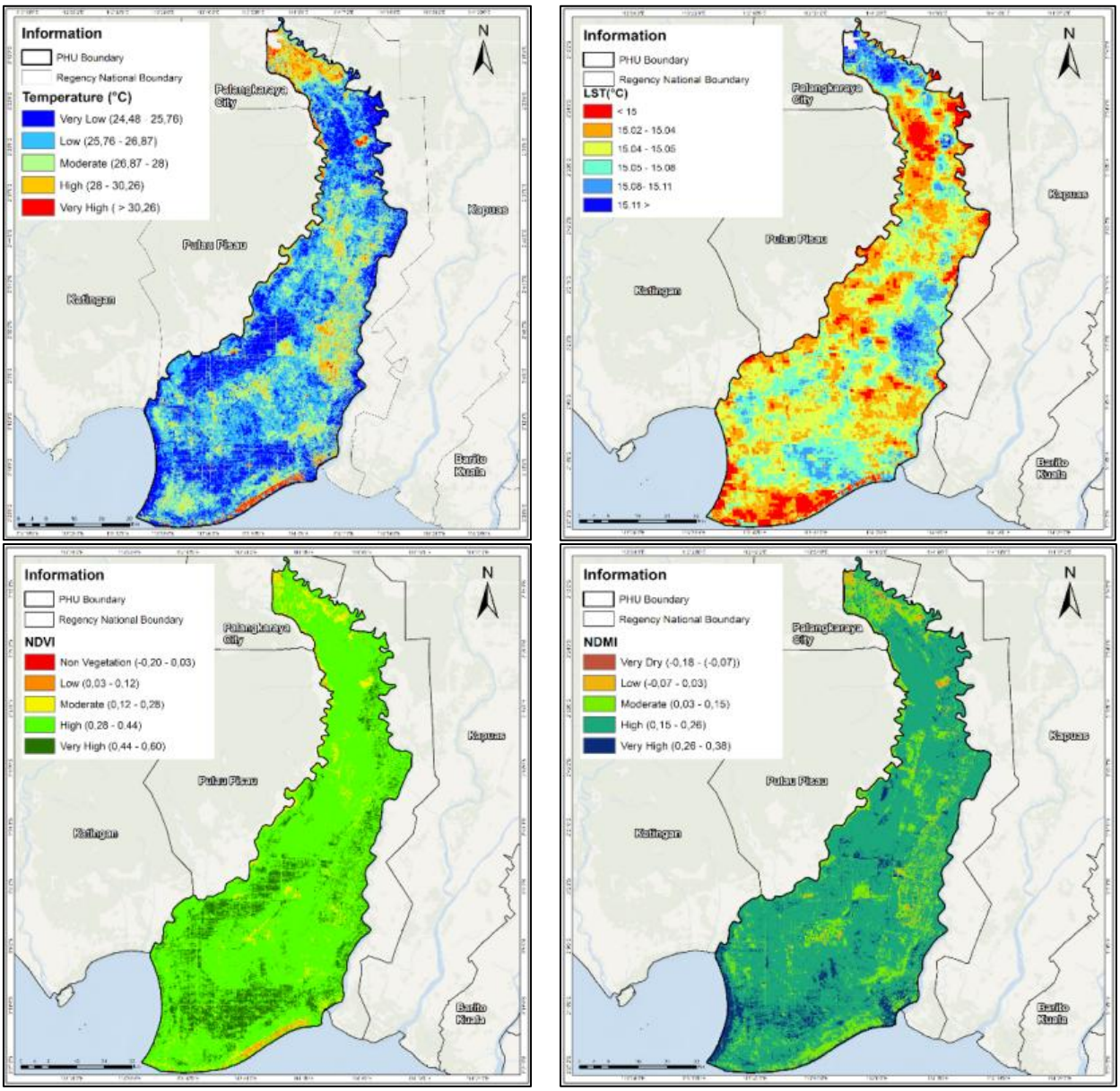



**Figure 7.** Forest fire variables (Topographic: Elevation, slope, aspect, TWI, TRI, and TPI; Meteorology: Rainfall, Wind speed, Temperature, and LST; Vegetation index: NDVI, NDMI, ANDWI, and NDBI) (Continue)

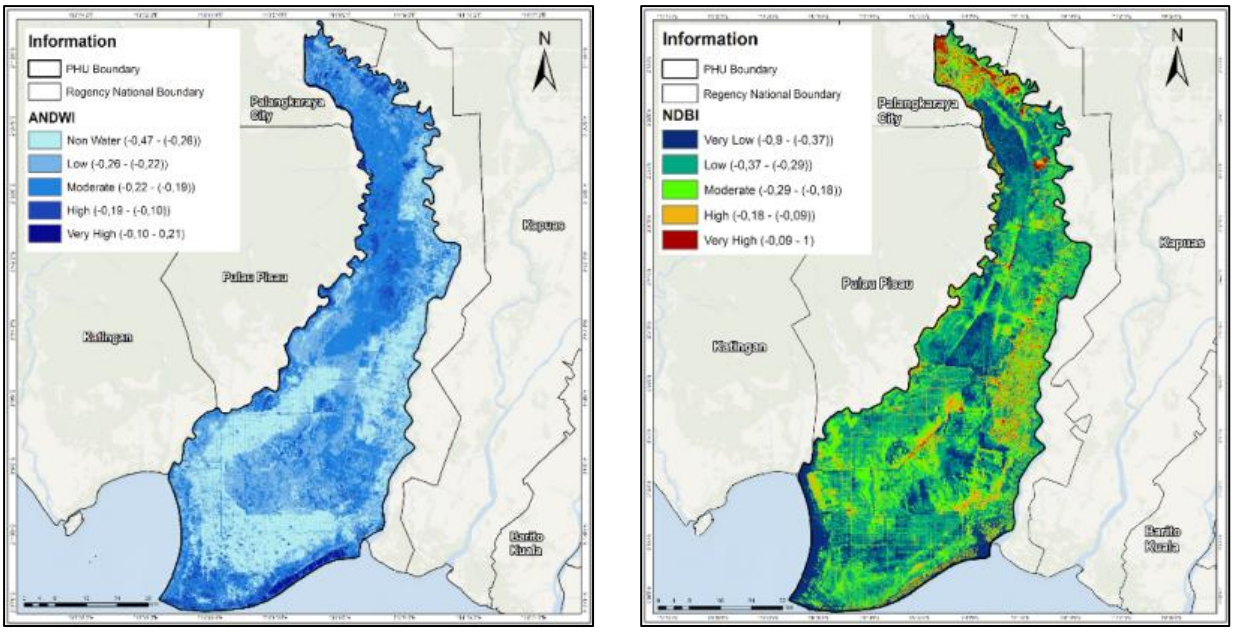



**Figure 7.** Forest fire variables (Topographic: Elevation, slope, aspect, TWI, TRI, and TPI; Meteorology: Rainfall, Wind speed, Temperature, and LST; Vegetation index: NDVI, NDMI, ANDWI, and NDBI) (Continue)

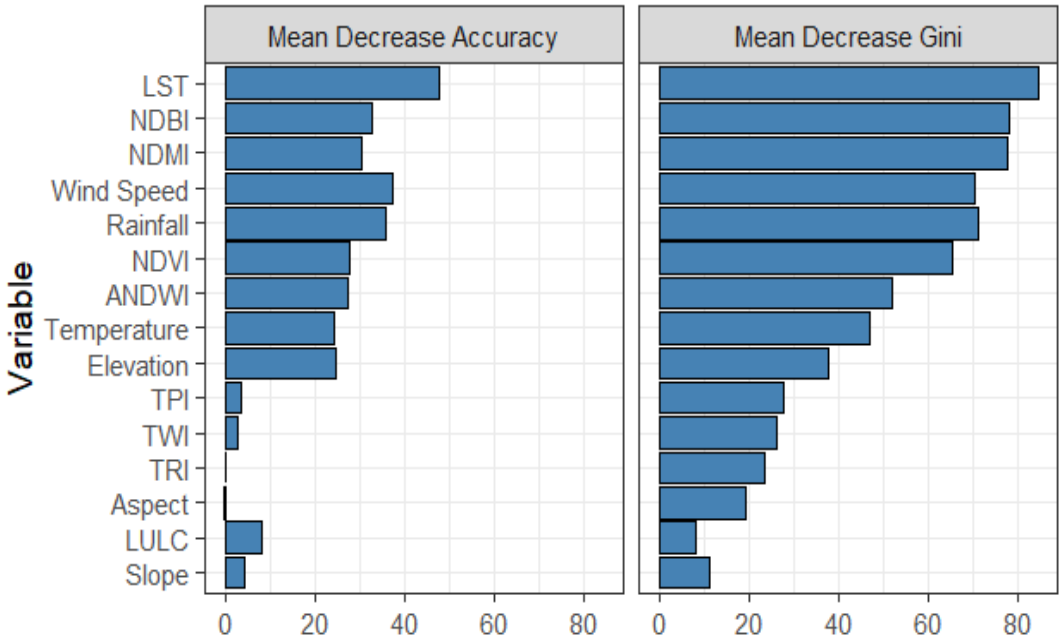



**Figure 8.** Mean Decrease Accuracy and Mean Decrease Gini by Random Forest model

fire-prone areas, typically achieving AUC values above 0.80. Similarly, Arabameri *et al.* (2022) emphasized that ROC and AUC are essential indicators for assessing the predictive performance of spatial models, particularly in forest fire risk management.

## Peatland Fire Susceptibility

Based on the spatial analysis of forest and land fire susceptibility Fig. 10, the study area exhibits a considerable variation in susceptibility levels. The very low susceptibility class dominates the region, covering

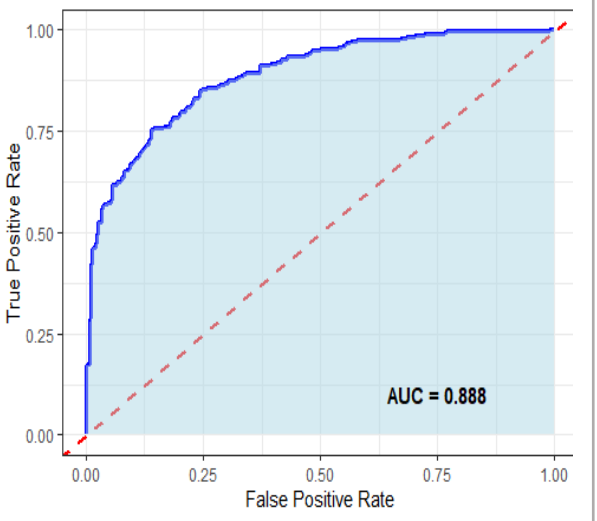



**Figure 9.** ROC and AUC for Random Forest probability model

an area of 143,994 ha, followed by the low class with 104,909 ha and the moderate class with 85,718 ha. Meanwhile, the high susceptibility class covers 58,541 ha, the very high class covers 40,597 ha, and the extreme class occupies 16,230 ha Table 2. The spatial distribution indicates that areas with high to extreme susceptibility levels are generally concentrated in the central to southern parts of the study area, represented by red to orange colors on the map. In contrast, areas with low to very low susceptibility levels are mostly distributed in the northern and western parts, illustrated in green. These findings emphasize that although the majority of the area falls within the low susceptibility category, the presence of zones with high to extreme susceptibility remains a significant concern for forest and land fire mitigation efforts.

## CONCLUSIONS

This study demonstrates that the Random Forest Probability method is capable of mapping peat fire susceptibility in the Kahayan–Sebangau Peat Hydrological Unit (PHU) with high accuracy (AUC > 0.85). The mapping results identified six susceptibility classes, namely very low (143,994 ha), low (104,909 ha), moderate (85,718 ha), high (58,541 ha), very high (40,597 ha), and extreme (16,230 ha). The key factors influencing susceptibility were found to be land surface temperature, rainfall, and vegetation condition. This information is essential for fire prevention, restoration planning, and sustainable peatland management in Central Kalimantan.

Monitoring of land fire hotspots in Riau was conducted from 2005 to 2023. Based on land type, hotspots were spread across two location types: KHG (peatland hydrological units) and non-KHG areas, with 138,523 hotspots (77.8%) in KHG areas and 39,583 hotspots (22.2%) in non-KHG areas. The highest number of hotspots was recorded in 2005 with 29,722 hotspots, and the lowest in 2022 with 827 hotspots. The decrease in hotspots over the years is attributed to the management of peatland damage, which has been addressed by the government, as well as policies that benefit peatland ecosystems. The use of FIRMS MODIS has proven effective in producing clear imagery for detecting hotspots. The distribution of hotspots is influenced by population size and, of course, the extent of KHG and non-KHG areas, with Pekanbaru having the fewest hotspots, while Rokan Hilir, Bengkalis, and Pelalawan have the highest, as they are predominantly KHG areas.

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