Assessing Peatland Fire Susceptibility Using GIS and Machine Learning in Riau Province, Indonesia

Sekarjati, D., Putklang, W.[*] and Wattanakij, N.
Geoinformatics, Department of Computer Science, College of Computing, Khon Kaen University, Khon Kaen City, 40000, Thailand
E-mail: dhanu.s@kkumail.com, putklang_w@kku.ac.th,[*] nagon@kku.ac.th
**Corresponding Author*

DOI: https://doi.org/10.52939/ijg.v21i10.4531

Abstract

Peatland fires represent a recurring environmental disaster in Riau Province, Indonesia, particularly during the dry season. This research aims to analyze the spatial distribution of peatland fire hotspots during the dry months from 2019 to 2023, and to predict peatland fire susceptibility in the dry season using a machine learning approach, while also identifying the most influential environmental and anthropogenic factors. This study employs the Global Moran's I to measure the spatial autocorrelation of peatland fire hotspot distribution and Forest-Based Classification and Regression (FBCR) to develop a machine learning-based prediction model, integrating spatial, meteorological, hydrological, and anthropogenic data. The results indicate that groundwater level (GWL) is a major contributing factor to peat fires, with a strong correlation between declining groundwater levels and increased fire risk. The FBCR model achieved an accuracy of 70–85%, successfully mapping the spatiotemporal distribution of peat fires, particularly during the dry season, when more than 60% of annual fire events occur. However, variations in the F1-score across different months suggest that the model can be further improved by addressing overfitting and incorporating real-time climate data. Future research should focus on developing ensemble learning or deep learning-based models to enhance prediction accuracy. Integration with high-resolution remote sensing technology and drone-based monitoring systems could further improve the model's ability to detect fire-prone areas.

Keywords: Forest-Based Classification and Regression, Machine Learning, Spatial Modeling, Peatland Fire Susceptibility

1. Introduction

Indonesia is one of the tropical countries with the largest peat ecosystems, particularly Riau Province, which contains an extensive peatland area crucial for global carbon sequestration, biodiversity, and local livelihoods [1] and [2]. However, these peatlands become highly susceptible to fire during the dry season [3]. Rewetting has been shown to reduce the frequency of wildfires in peatland areas [4]. In 2019, over 857,000 hectares of land were affected by fires in Indonesia, with Riau accounting for approximately 18% of the total burned area [5], causing significant economic losses and ecological damage [6]. Peatland fire events in Riau Province peaked in 2019, declined significantly until 2022, but then resurged in 2023, underscoring their persistent and fluctuating threat. Following the 2019 peak, the burned area decreased substantially, with approximately 15,000 hectares affected in 2020 [7]. This decline continued in 2021 (1,235 hectares) and 2022 (1,219 hectares) before the area increased again in 2023 to 2,632 hectares [8] and [9]. This observed pattern clearly indicates that, despite periods of reduction, peatland fires remain a recurring and significant challenge in Riau Province.

Peatland fires are driven by a complex interplay of dynamic natural factors, such as rainfall, soil moisture, wind, and air temperature, and exacerbated by anthropogenic factors like land clearing, unsustainable agriculture, and burning for land rejuvenation [10] and [11]. These events, exemplified by the 2015 haze disaster, lead to significant PM2.5 and CO2 emissions, posing international concerns [12][13] and [14]. The complex interactions between these factors make predicting peatland fires a significant challenge, necessitating an integrated scientific approach, particularly given the susceptibility of Riau's peatlands to hydrological disturbances from extended dry seasons and extensive canal networks that lower water tables and accelerate peat oxidation [11][15[16][17][18] and [19].

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Advanced technologies like machine learning (ML) are highly relevant for identifying patterns and critical fire contributing factors [20]. Forest-Based Classification and Regression (FBCR) is an effective ML approach for environmental studies, capable of modeling non-linear relationships and identifying variable importance [21] and [22]. Its flexibility, resistance to overfitting, and ability to simultaneously process vector and raster data make FBCR particularly suitable for geospatial fire prediction in complex peatland ecosystems [11]. This study implements FBCR for susceptibility mapping, which generates a spatial classification of areas with varying fire potential. By focusing on dry-season dynamics and integrating climatic, hydrological, and anthropogenic variables, the model provides a more distinct and accurate understanding of environmental factors influencing fire [23] and [24]. Most previous peatland fire studies focus on climate, often overlooking hydrological and human factors, limiting local scale modeling. FBCR, a GIS-based machine learning method that handles raster and vector data and captures non-linear relationships, is rarely applied. This study integrates climatic, hydrological, and anthropogenic variables in FBCR to better identify fire-prone areas in Riau Province.

Therefore, this study aims to analyze the spatial distribution of peatland fire hotspots during the dry months from 2019 to 2023, and to predict peatland fire susceptibility in the dry season using a machine learning approach, while also identifying the most influential environmental and anthropogenic factors. The findings will offer valuable insights for sustainable peatland management, inform fire mitigation policies, contribute to global efforts in reducing greenhouse gas emissions, and the methodology can be applied to other regions, thus advancing the scientific literature on spatially explicit peatland fire susceptibility assessment.

2. Methodology

2.1 Study Area

Riau Province contains one of the largest peatland areas in Indonesia, covering approximately 4.9 million hectares in total (Figure 1) [25]. Riau Province has a humid tropical climate with annual rainfall of 2,000–3,000 mm [4]. Its terrain is largely lowland plains and peat domes intersected by rivers and swamps, while the west rises to hills and mountains up to 1,200 m [26]. This flat peatland topography creates fragile hydrological conditions, making the region highly vulnerable to drainage and seasonal rainfall shifts [26]. These ombrogenous peatlands, accumulated over millennia to depths exceeding 10 meters, store vast amounts of carbon and possess unique soil properties [27] and [28]. Consequently, they are critical for global climate change mitigation, hydrological regulation, and support diverse flora (e.g., Shorea spp.) and endangered fauna like Panthera tigris sumatrae [29][30][31][32][33] and [34].

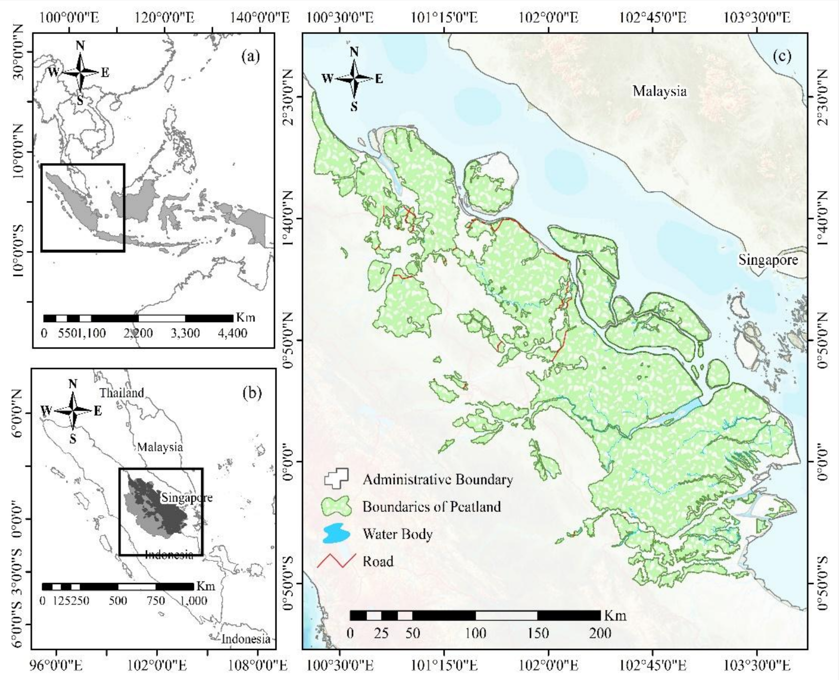

Figure 1: Location of research (a) Indonesia, (b) Riau province, and (c) Boundaries of peatland

However, Riau's resource-based economy, largely driven by oil, natural gas, and the extensive growth of oil palm plantations, directly impacts these vital ecosystems. By 2020, nearly 45% of Riau's peatlands were covered by oil palm [35]. This rapid expansion, involving land conversion and drainage for agriculture, significantly increases fire susceptibility, identifying human activities as a primary driver of regional fire risk.

2.2 Research Framework

This study was designed through a structured research framework that integrates data collection, preprocessing, modeling, and analysis into a coherent workflow. The framework highlights how environmental and anthropogenic variables were processed and incorporated into the Forest-based Classification and Regression (FBCR) model to predict peat fire susceptibility. The overall sequence of the research stages is presented in the flowchart (Figure 2).

2.3 Data Collection

In this study, the data collection was carried out by considering various environmental parameters that contribute to fire dynamics in peatlands. The observation period focused on the dry months, specifically February, March, July, August, September, and October. The study focused on fire dynamics in peatlands during the dry months (February, March, July, August, September, October). This period, characterized by elevated temperatures, low humidity, and declining groundwater levels, significantly increases fire risk due to accelerated peat desiccation. Historically, these months represent Riau Province's highest fire susceptibility, a fact supported by the Riau Provincial Environment and Forestry Agency's regional environmental issue analysis report [36]. The climatological dataset utilized includes atmospheric variables such as humidity, temperature, and rainfall. Humidity and temperature data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) via the website https://www.ecmwf.int/. Rainfall data were sourced from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), which can be downloaded from https://www.chc.ucsb.edu. This data served as the target variable in the predictive model. Hydrological parameters, such as groundwater levels, were obtained from field observations conducted by the Peatland and Mangrove Restoration Agency of the Republic of Indonesia (BRGM). Additionally, supporting spatial data, including the presence of road and river networks, were acquired from the Geospatial Information Agency (BIG) through the website https://tanahair.indonesia.go.id. Finally, land use data were obtained from the Land Use/Land Cover (LULC) time series dataset with a 10-meter resolution, published by ESRI Land Cover and derived from Sentinel-2, accessible via https://livingatlas.arcgis.com. All these datasets were utilized as environmental factors influencing peat fire dynamics (see Table 1).

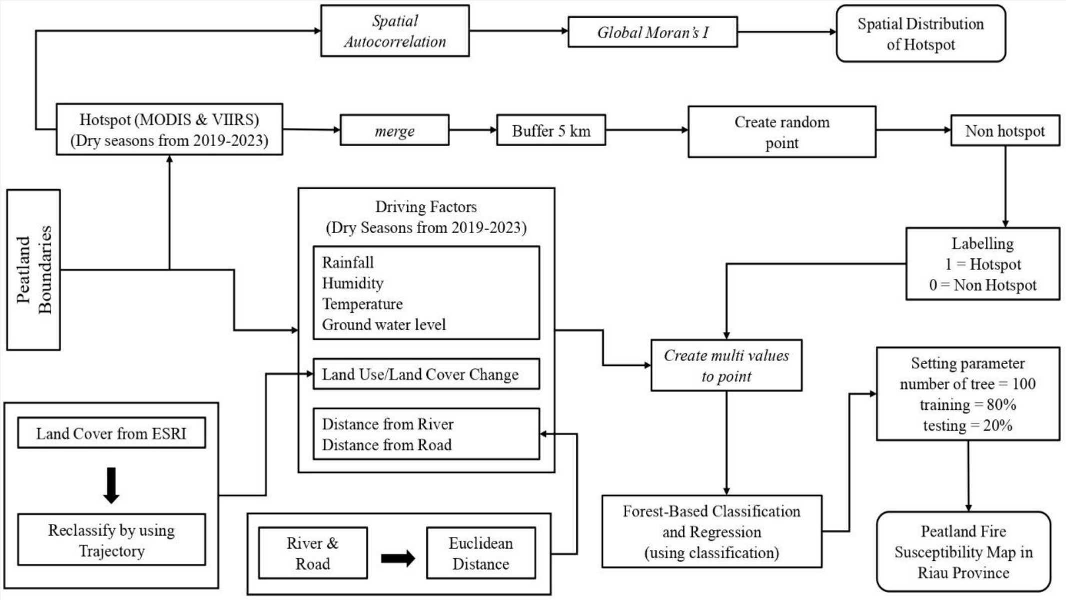

Figure 2: Peatland fire susceptibility assessment methodology

Table 1: Data characteristics and Sources used in the research

Dataset	Type	Scale or Resolution	Year	Product
Hotspot	Point	1 km	2019 - 2023	VIIRS and MODIS
Humidity	Raster	0.25° x 0.25°	2019 - 2023	ECMWF
Temperature	Raster	0.25° x 0.25°	2019 - 2023	ECMWF
Rainfall	Raster	0.05° x 0.05°	2019 - 2023	CHIRPS
Ground Water Level	Vector	1:100	2019 - 2023	BRGM
Road	Vector	1:50,000	2021	BIG
River	Vector	1:50,000	2021	BIG
Land Use/Land Cover	Raster	10 meters	2019 - 2023	LivingAtlas - ESRI

The research utilized both raster and vector data with varying resolutions. Raster data (temperature, humidity, rainfall) had spatial resolutions from 0.05° to 0.25°, while Land Use/Land Cover (LULC) data from ESRI Living Atlas (ESRI 2020) was at 10 meters. Vector data, such as road and river networks, were at 1:50,000, and groundwater levels at 1:100. All datasets underwent preprocessing, including re-projection to a uniform coordinate system and resampling to a consistent spatial resolution. Specifically, all raster datasets were resampled to a consistent 100-meter spatial resolution for compatibility and accurate integration, while Euclidean distance was used to process river and road data to measure proximity to peatland fire occurrences. This method, commonly applied in spatial fire susceptibility studies, effectively captures the influence of human accessibility (roads as entry points for activities like land clearing) and peat drying (rivers as drainage networks), both critical drivers of peatland fire risk.

For the development of the peat fire prediction model, this study applied the Forest-based Classification and Regression method, which facilitates the exploration of complex relationships between environmental parameters and event data [37]. The model was used to classify fire-prone areas and predict the probability of fire occurrence based on a combination of environmental variables. Through this approach, the research aims to enhance the understanding of peat fire dynamics by incorporating the driving factors of occurrence, as well as providing more accurate, data-driven information to support fire mitigation and management efforts in Riau's peatlands.

2.4 Data Processing and Analysis

2.4.1 Peatland fires Hotspot in 2019 to 2023

Data on peatland fire occurrences for this study were obtained from satellite imagery provided by the Visible Infrared Imaging Radiometer Suite (VIIRS) and the Moderate Resolution Imaging Spectroradiometer (MODIS), both offering a spatial resolution of 1 km. The fire occurrence data are publicly accessible at https://www.earthdata.nasa.gov. Non-hotspot data were generated via random sampling using a 1:1 ratio relative to hotspot occurrences for each dry season. To ensure spatial independence, a 5 km buffer was applied around fire points to minimize spatial autocorrelation and ensure that non-fire samples reflected distinct environmental conditions. This spatial separation enhances the contrast between classes, improving model accuracy and reducing bias in classification [38]. This method was consistently implemented for the months of February, March, July, August, September, and October. The dataset illustrates distinct annual and monthly patterns in fire incidence, providing a valuable foundation for modeling and predictive analysis using Forest-based Classification and Regression methods to enhance the understanding of peatland fire dynamics in Riau.

2.4.2 Hotspot distribution analysis

Spatial Autocorrelation: To deepen the understanding of hotspot distribution, spatial autocorrelation was applied to assess whether fire occurrences form clustered, dispersed, or random patterns. This analysis is crucial for revealing the spatial structure of peatland fires. Global Moran's I was used to measure the spatial autocorrelation of peatland fire hotspot distribution in the study area. This statistic quantifies the degree to which similar values are spatially clustered, dispersed, or randomly distributed. Values range from -1 to +1, where positive values indicate clustering, negative values indicate dispersion, and values near zero suggest a random pattern. The analysis was conducted using ArcGIS Pro's Spatial Autocorrelation tool, with hotspot point data as the input feature and inverse distance as the conceptualization of spatial relationships.

2.4.3 Environmental and anthropogenic variables

2.4.3.1 Meteorological variables

Rainfall: Rainfall is a key meteorological parameter affecting peatland fire dynamics, particularly during the dry season when reduced precipitation lowers peat moisture and increases fire risk. Monthly accumulated rainfall data for the dry-season months (February, March, July, August, September, and October) from 2019 to 2023 were obtained from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) product in raster format. The datasets were clipped to the peatland boundary of Riau Province, reprojected to WGS 1984 UTM Zone 47N, and resampled to a 100-meter resolution with standardized grid alignment using a Snap Raster reference. The processed rainfall rasters were subsequently used as predictor variables in the FBCR model.

Relative Humidity: Relative humidity was selected as a key climatological variable due to its influence on peatland fire susceptibility. Monthly data from ECMWF reanalysis (NetCDF format) covering 2019–2023 were converted into point features (1,558 points) using the *XY Table to Point* tool, checked for null values, and standardized to the WGS 1984 UTM Zone 47N coordinate system. As the dataset consisted of point-based observations with uneven spatial coverage, Inverse Distance Weighting (IDW) interpolation was applied to generate continuous humidity surfaces across the study area. The resulting rasters were incorporated as predictor variables in the FBCR model, and humidity values were extracted at hotspot points for further analysis.

Temperature: Monthly surface temperature data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) for the period 2019–2023. The datasets, provided in raster format, were processed using the same workflow as relative humidity, including conversion to point features (1,558 points) and spatial interpolation through the Inverse Distance Weighting (IDW) method to generate continuous surfaces at 100-meter resolution. This step ensured consistency in pixel size, projection, and spatial extent with other raster datasets such as precipitation, land cover, and distance-based variables. All rasters were subsequently reprojected and clipped to the boundaries of peatland areas in Riau Province, after which temperature was incorporated as a predictor variable in the FBCR model.

2.4.3.2 Hydrological

Ground Water Level (GWL): Daily GWL data from 52 field stations were obtained in point format and pre-processed to remove anomalies and adjust the projection. The point data were interpolated into raster surfaces using the Inverse Distance Weighted (IDW) method in ArcGIS Pro at a 100-meter resolution, ensuring consistency with other environmental variables. The resulting rasters represent groundwater depth relative to the surface and were used as explanatory variables in the FBCR model to assess peatland fire susceptibility.

2.4.3.3 Anthtopogenic

Land Use/Land Cover Change: Land use data was obtained from satellite imagery for the annual period from 2019 to 2023, using the original classification. Reclassification was necessary to simplify the diverse land use classes into categories more relevant to peatland fire risk. Additionally, in the seasonal analysis, relying solely on annual data would prevent the model from capturing land use changes occurring specifically during the dry season. The initial land cover data (from ESRI Living Atlas) was processed to derive land use/land cover change (LULC change) information for the period 2019–2023 through trajectory analysis and reclassification. LULC change was used instead of static land cover because it captures recent transitions such as deforestation, agricultural expansion, or land degradation that alter fuel availability and microclimatic conditions, thereby increasing fire susceptibility [2]. In peatlands, such changes often involve drainage and vegetation clearance, accelerating peat drying and raising ignition risk. Incorporating multiyear change data allows the model to reflect these dynamic processes, which have been identified as major drivers of peatland fires in previous studies [39] and [40].

To address this, land use maps from the study period (2019–2023) were integrated using a raster overlay technique in GIS, followed by interpretation to classify land use/land cover changes. LULC change within a landscape can be characterized by two key dimensions: the direction of change, referring to whether land cover types transition in similar or divergent ways, and the magnitude of change, which reflects the extent or scale of the transformation [41]. The use of trajectory-based land use change maps adds significant value to peatland fire prediction analysis [39]. Unlike approaches that rely solely on annual land use data, this method provides a temporal context for understanding land use dynamics. Thus, reclassifying land use changes not only simplifies the input variables in the Random Forest model but also enhances the model's sensitivity in identifying areas with high fire potential based on land change patterns.

LULC change between 2019 and 2023 was derived from annual ESRI Living Atlas land use maps, reclassified into six classes using a trajectory-based approach, where the land cover class of each pixel is compared year by year to record the sequence of transitions, and analyzed through raster overlay to produce a map of pixel-level changes. The original land cover classes (Tree, Crop, Waterbody, Bare land, Rangeland, Flood vegetation, and Built-up) were reclassified into trajectory-based categories (no change, deforestation, cultivation, urbanization, land degradation, and reforestation) as input for the FBCR model.

LULC change trajectories from 2019 to 2023 were generated to capture detailed transitions between land cover types. Trajectory-based land use change maps significantly enhance our fire susceptibility model by capturing dynamic landscape evolution, improving predictive precision. Because it identifies high-risk transformation signatures, such as deforestation to agriculture, which directly indicate active practices like slash-and-burn and highlight immediate ignition and spread zones [40]. This approach is increasingly advocated in wildfire modeling literature [39] and [42]. These trajectories were used solely for reclassification, producing five simplified categories: no change, deforestation, cultivation, urbanization, and land degradation. Representative trajectory patterns are shown in Table 2, while the FBCR model employed only the simplified categories as input. This approach reduces data complexity, minimizes class imbalance, and improves computational efficiency when processing large datasets, while still capturing the dominant land use transitions that influence peatland fire susceptibility.

To ensure the reliability of the trajectory data derived from land use categories over the 2019–2023 period, this study conducted an accuracy assessment an essential step in the utilization of land use data. The evaluation employed a confusion matrix, which includes producer's accuracy, user's accuracy, and overall accuracy, as a basis for assessing classification performance. This approach helps to minimize classification errors in the development of land use change trajectories. A total of 450 reference (ground truth) points were generated using stratified random sampling across each land use change trajectory class. These points were used to evaluate the classification accuracy for the entire observation period (2019–2023). The validation process utilized high-resolution remote sensing data, including detailed interpretation of Sentinel-2 imagery, Google Earth imagery, and the World Imagery basemap provided by ESRI. The combination of these high-resolution sources enhances the precision of the accuracy assessment. The accuracy metrics were calculated using the following Equations 1:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

Equation 1

Where κ represents the Kappa coefficient, P_o is the proportional of observed agreement and P_e is the proportion of agreement expected by chance.

Distance from River and Distance from Road: In this study, distance to rivers and roads were included as static spatial predictor variables, given the relative stability of river courses and major road networks in Riau between 2019 and 2023. Both variables serve as proxies for anthropogenic influence and ignition potential, reflecting accessibility, land conversion pressure, and human intervention. River distance was derived from river shapefiles converted to raster and processed using the Euclidean Distance tool, enabling the identification of areas far from water sources that are more vulnerable to peat fire risk. All datasets were standardized to WGS 1984 UTM Zone 47N to ensure spatial consistency. Euclidean distance was used to measure proximity to roads and rivers because it is widely applied in fire susceptibility studies and effectively represents human access and potential ignition sources at large scales [39].

Table 2: Trajectory-based LULC change reclassification in the study area

LULC change	**Definition**	**LULC Trajectory***
No change	Unchanged land use	TTTTT, CCCCC
Deforestation	Forest converted to other land uses	TTCCC, TRCCC
Cultivation	Non-cultivation land converted to agriculture	RRCCC, RCCCC
Urbanization	Expansion of urban areas	TUUUU, RUUUU
Land degradation	Vegetation loss or negative land use change (e.g., to bare land)	RTRRR, RFFFF
Reforestation	Restoration of previously cleared or degraded forest areas, either naturally or through human intervention.	RTTFT, BTRRR, WTTTT

** The sequence represents the time periods 2019, 2020, 2021, 2022, and 2023.*
T (Trees), C (Crop), B (Bare Ground), F (Flood Vegetation), R (Rangeland), U (Built Area), W (Water Body)
**Only representative trajectory patterns are shown to illustrate the reclassification logic, while the model used the simplified land use categories as input*

Roads facilitate activities like land clearing and accidental burning, while rivers influence drainage and peat drying, both key fire drivers. This method is computationally efficient for large FBCR datasets, though it oversimplifies actual accessibility and hydrological connectivity. Future studies could use network-based or hydrologically informed measures for greater accuracy.

2.4.4 Peatland fire susceptibility assessment

2.4.4.1 Pearson correlation analysis

To examine potential multicollinearity among predictor variables, we conducted a Pearson correlation analysis. The Pearson correlation coefficient (r) measures the strength and direction of linear associations between two continuous variables, ranging from –1 (perfect negative correlation) to +1 (perfect positive correlation), with values near 0 indicating weak or no linear relationship [43]. The analysis was applied to all environmental and anthropogenic predictors, namely humidity, temperature, rainfall, groundwater level (GWL), distance from rivers, distance from roads, and land use/land cover change (LULCC). Because peatland fire dynamics are strongly influenced by seasonal variability, the correlations were calculated separately for each dry month (February, March, July, August, and September). This procedure allowed us to identify pairs of variables with substantial correlations that could indicate multicollinearity and to better understand the potential interactions among predictors.

2.4.4.2 Forest-based classification and regression

In this study, the Forest-based Classification and Regression algorithm is employed as a predictive model to track peatland fire dynamics. Forest-based Classification and Regression is an ensemble learning technique that combines multiple decision trees to enhance prediction accuracy and mitigate overfitting [44] and [45]. In this approach, each decision tree is constructed based on a random subset of the training data, and the selection of features (variables) is also randomized for each tree [46]. This randomization reduces the correlation between the individual trees and increases the model's robustness against overfitting [47]. Peatland fire susceptibility was modeled using the Forest-based Classification and Regression (FBCR) tool in ArcGIS Pro, which implements the random forest algorithm. FBCR hyperparameters were tuned through trial runs, testing the number of trees (50–250), maximum features, and minimum samples per leaf. An optimal setting of 100 trees was selected to balance accuracy and computational efficiency. Ten validation runs were performed to minimize bias from random sampling, while parameter tuning followed ArcGIS Pro’s default configuration, which is validated for spatial modeling. The FBCR tool also generated variable importance scores, quantifying each predictor’s contribution by measuring the increase in prediction error after variable permutation. Candidate predictors were iteratively tested, and those that consistently reduced validation accuracy were excluded, thereby reducing redundancy and multicollinearity. This study applies FBCR in the context of peatland fire susceptibility, an approach that has been rarely explored, demonstrating its ability to capture nonlinear interactions between environmental conditions and land use dynamics.

2.4.4.3 Accuracy assessment

Model performance was evaluated using overall accuracy and the F-1 score, the latter providing a balanced measure of Precision and Recall, particularly important in the presence of class imbalance [48] and [49]. These metrics were derived directly from the FBCR output in ArcGIS Pro, ensuring an objective assessment of the model’s predictive reliability. The inclusion of diverse environmental and anthropogenic predictors such as temperature, humidity, rainfall, groundwater level, roads, rivers, and land use/land cover change enabled the model to capture complex, nonlinear interactions influencing peatland fire susceptibility.

3. Results and Discussion

3.1 Hotspot Distribution

Spatial autocorrelation: The spatial analysis of peatland fires is essential for understanding hotspot distribution patterns and their interrelationships within the observation area. A quantitative approach that can be employed to analyze fire distribution patterns is spatial autocorrelation analysis using Moran's I Index. This method enables the identification of fire hotspot distribution patterns whether clustered, dispersed, or random based on the spatial relationships between area units [50]. In the context of peatland fires, understanding these spatial patterns is crucial for developing more effective, data-driven mitigation strategies [51].

Spatial autocorrelation analysis using Global Moran’s I was conducted to assess whether predicted fire susceptibility patterns exhibit spatial clustering. The results show positive Moran’s I values for most dry season months, indicating that peatland fires tend to cluster spatially rather than being randomly distributed (Table 3).

Table 3: Spatial autocorrelation in the observation time period

Months	Moran's I	z-score	p-value	Interpretation
February	0.138	10.228	0.000	Clustered
March	0.121	8.371	0.000	Clustered
July	0.078	5.449	0.000	Clustered
August	0.018	1.353	0.175	Random
September	0.075	5.386	0.000	Clustered
October	0.055	5.155	0.000	Clustered

This suggests that certain areas share similar environmental and anthropogenic conditions influencing fire risk. In some months, clustering is more pronounced, reflecting persistent fire-prone conditions in degraded or plantation-dominated peatlands. This suggests that fires tend to occur in geographically proximate locations, likely influenced by environmental factors in peatlands [52], land clearing practices through burning [53], and the lack of fire control infrastructure [54]. This pattern underscores the need for landscape-based fire management, prioritizing fire prevention in high-risk areas as a key mitigation strategy.

In (d) August, a higher p-value (0.175) indicates that the hotspot distribution pattern does not exhibit significant spatial trends and can therefore be categorized as random. This suggests that fires are more widely distributed, potentially influenced by peat soil moisture variability, seasonal weather conditions, or the effectiveness of early monitoring systems that prevent fire concentration in specific locations [55].

Clustered patterns in peatland fires are often associated with homogeneous environmental conditions, such as the presence of combustible fuels (dry peat litter), climatic influences (El Niño and strong winds), and human activities that trigger fires [56]. In contrast, a scattered pattern in Moran's I index may reflect natural variability between regions, including differences in peat moisture levels or the success of fire mitigation efforts that inhibit fire spread [57]. Previous studies have indicated that peat fires tend to recur in the same locations due to cyclical land degradation and drainage via canal systems, which accelerate peat moisture loss [58] and [59]. These findings highlight the importance of spatially targeted fire mitigation strategies, such as the establishment of priority zones for peatland ecosystem restoration and the development of satellite-based early fire detection systems. The results of this spatial autocorrelation analysis confirm that understanding hotspot distribution patterns is essential for effective peat fire mitigation and confirm that spatial dependency is an important characteristic of peatland fire occurrence in Riau Province and should be accounted for in susceptibility modeling. A spatial data-driven approach enhances targeted policy planning, whether in fire prevention, fire suppression, or peat ecosystem restoration efforts.

Fire Hotspots during the Dry Season: The analysis of peatland fire hotspots from 2019 to 2023 reveals notable interannual variations in both frequency and seasonal distribution. The utilization of VIIRS and MODIS satellite data facilitated the spatial and temporal identification of fire events across Riau Province. These results highlight the severity of fire occurrences during extreme years and the subsequent decline in incidents in the following periods (Figure 3).

In 2019, peatland fires reached their peak severity during the study period, with 27,947 hotspots detected (Table 4). The temporal pattern exhibited pronounced peaks in September (11,198 incidents) and August (5,963 incidents), coinciding with an extended dry season driven by El Niño conditions. The distribution map shows widespread concentrations of hotspots across the central and eastern peatland areas, confirming that 2019 was an extreme fire year that serves as a benchmark for subsequent analyses. In contrast, fire incidents in 2020 declined substantially to 3,221, with most events occurring in March (1,905) and February (1,000). This reduction was associated with the absence of strong El Niño conditions and higher rainfall during the latter half of the year. The distribution map illustrates a more fragmented pattern, with smaller hotspot clusters primarily located in the western part of the peatland area. A similar pattern was observed in 2021, when 2,890 hotspots were recorded, mainly in March (1,115) and February (982). Although the overall number of incidents decreased, the persistence of early dry season fires suggests that burning remains an entrenched land management practice, particularly in smallholder agriculture and along plantation edges.

The downward trend continued in 2022, when only 578 hotspots were detected. Unlike previous years, the peak occurred in July (233) and March (139), and the distribution map shows that fires tended to be localized rather than widespread.

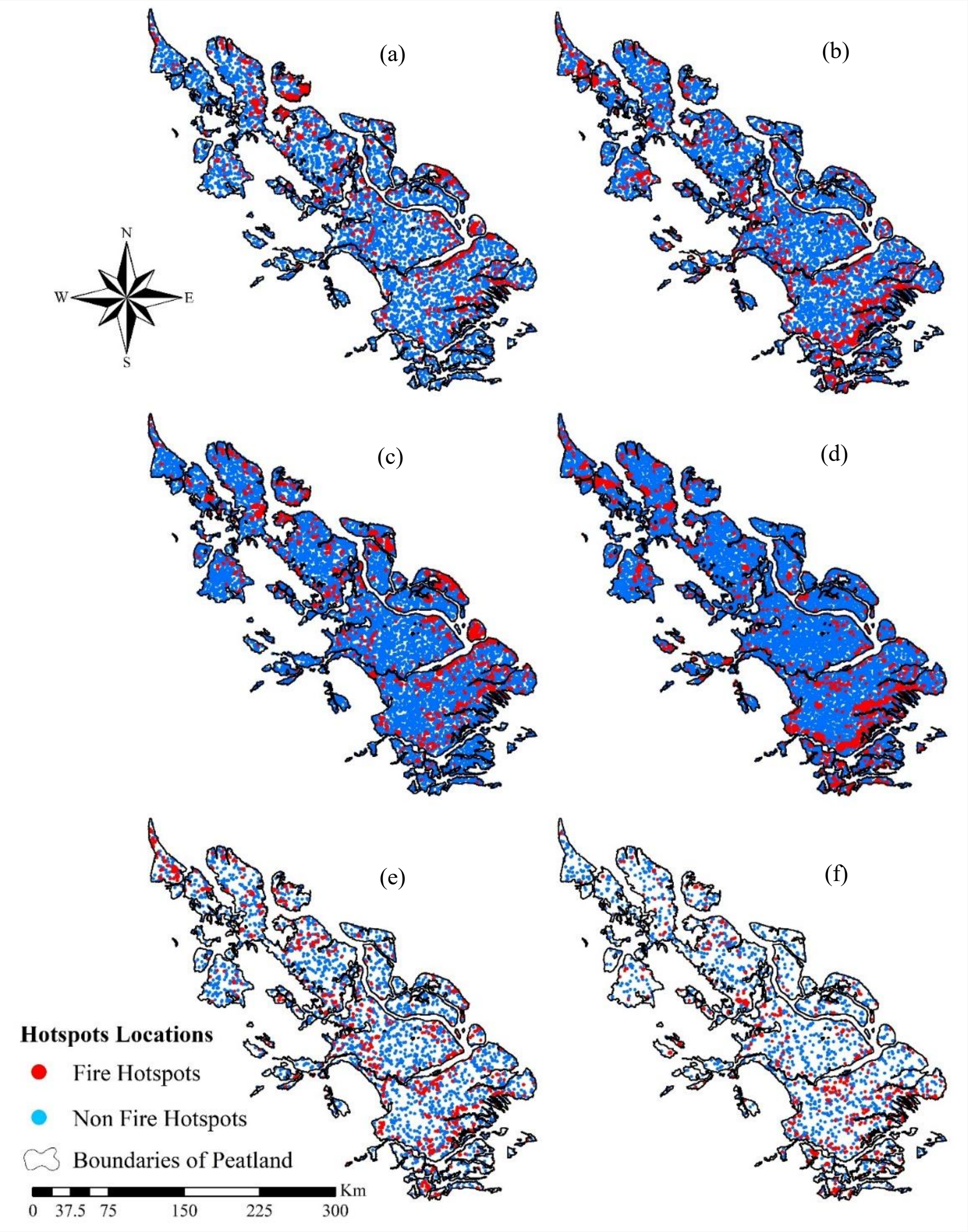

Figure 3: Total fire hotspots in 2019-2023 in the months (a) February, (b) March, (c) July, (d) August, (e) September, (f) October

Table 4: Number of fire hotspot in 2019 until 2023

Years	Hotspot					
	February	March	July	August	September	October
2023	22	173	157	277	284	473
2022	68	139	233	97	27	14
2021	982	1,115	438	87	128	140
2020	1,000	1,905	87	147	37	45
2019	3,041	5,795	1,208	5,963	11,198	742
Total	5,113	9,127	2,123	6,571	11,674	1,414

In 2023, however, fire activity rebounded slightly, with 1,386 hotspots detected. The highest concentrations occurred in October (473 incidents) and September (284 incidents), reflecting a return to the late dry season susceptibility pattern. Although the magnitude of fire activity was considerably lower than in 2019, the recurrence of late-season fires highlights the persistent susceptibility of Riau's peatlands to burning during extended dry periods.

3.2 Environmental and Anthropogenic Variables

3.2 1 Anthropogenic

Land Use/Land Cover Change: The analysis of land use and land cover (LULC) dynamics provides an essential perspective for understanding the drivers of peatland fire susceptibility in Riau Province. Land use data were derived from annual satellite imagery spanning the period 2019 to 2023, and subsequently reclassified to reduce complexity and highlight categories most relevant to fire risk. By simplifying the categories into broader classes such as deforestation, cultivation, urbanization, land degradation, and reforestation the analysis becomes more effective in linking land cover transitions to fire dynamics (Figure 4).

The land use/land cover classification of the study area between 2019 until 2023 reveals significant changes with implications for peatland fire dynamics. As shown in Table 5, approximately 84.20% of the observed area remained unchanged, indicating the dominance of stable land cover/land cover. However, the remaining 1.39% underwent land use changes that may influence the occurrence and severity of peat fires. Deforestation accounts for 8.63% of the changes, primarily due to the conversion of forests to other land uses, mainly for agricultural expansion and land clearing activities. This process increases the susceptibility of peat soils to oxidation and drying, thereby elevating fire risk.

Additionally, agricultural cultivation expanded by 4.01%, primarily for plantations and other agricultural sectors. Drainage systems implemented in these areas lower the water table, making peatlands more flammable during the dry season. Although urbanization remains relatively small, it exhibits a growing trend of land conversion, which can contribute to habitat fragmentation and alter regional hydrological dynamics. Furthermore, land degradation is a critical concern, as degraded peatlands often become fire-prone hotspots due to reduced water retention capacity. Conversely, reforestation efforts represent important ecological restoration initiatives aimed at mitigating fire risk.

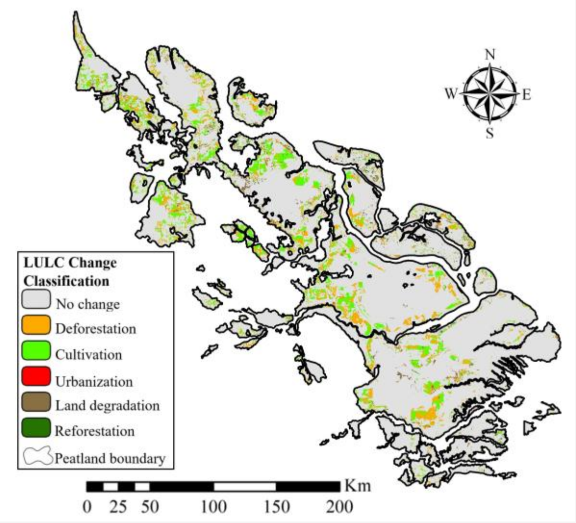

Figure 4: Map of land use/land cover change categories in 2019-2023

Table 5: Area and percentage land use/land cover categories in 2019-2023

No	Classification	Area (km)	(%)
1	No change	6,262.21	84.20
2	Deforestation	641.59	8.63
3	Cultivation	298.45	4.01
4	Urbanization	4.91	0.07
5	Land degradation	103.54	1.39
6	Reforestation	126.59	1.70

Given the critical role of land use and land cover information in understanding peatland fire dynamics, it is essential to verify the accuracy of the classification results. An accuracy assessment was therefore performed using trajectory data to evaluate the consistency of the reclassified categories with observed land use changes. The land use classification applied in this study includes six categories: no change (NoCh), deforestation (De), cultivation (Cu), urbanization (Ur), land degradation (LanDeg), and reforestation (Re), within the peatland ecosystem of Riau Province (Table 6).

The classification evaluation based on land use trajectory analysis yielded an overall accuracy of 98%, while the Kappa coefficient, which measures the agreement between the classification results and reference data, reached 0.93. Minor discrepancies were observed in both user's and producer's accuracy for certain land use classes. The high overall accuracy can be attributed to the integration of Sentinel-2 imagery, Google Earth imagery, and the high-resolution ESRI World Imagery basemap, which enhanced the detection of actual land use conditions in the field. Furthermore, the accuracy assessment results provide a robust foundation for the application of this classification in peatland fire prediction, thereby reinforcing its role as a critical input variable in the machine learning-based predictive modeling conducted in this study.

Distance from River and Road: The distance from rivers ranges from 0 to 58,405 m, with the closest zones concentrated along the main river networks in the northern and central parts of the study area. Areas represented in green to yellow indicate peatlands located near river systems, which play a critical role in regulating hydrology and maintaining peat moisture conditions. In contrast, darker-colored areas are situated farther from river channels, reflecting reduced hydrological influence and greater susceptibility to seasonal drying (Figure 5). The distance from roads varies between 0 and 16,300 m, with the highest road network density observed in central and eastern Riau. The map indicates that most peatlands are situated relatively close to roads, as reflected by the predominance of yellow and orange zones. These areas are more accessible and, therefore, more vulnerable to anthropogenic activities such as land clearing, agricultural expansion, and fire ignition. Conversely, peatlands located farther from roads, shown in darker shades, are generally less disturbed, although they may still be indirectly affected by fire spread from more accessible areas.

3.2.2 Meteorological and hydrological variables

The spatial variation of humidity in Riau Province shifts during the dry season. In February and March, higher humidity is concentrated in the northern region, consistent with relatively higher rainfall and shallower groundwater levels. By August and September, higher humidity appears in the southern region, reflecting localized increases in rainfall and the persistence of groundwater levels that sustain moisture availability. In contrast, temperature shows a more uniform spatial distribution across the province, with only minor local variations (Figure 6). This pattern reflects the dominant role of atmospheric moisture and hydrology in driving spatial variability, whereas temperature remains relatively consistent. GWL maps show declining water tables from June (–0.3 to –0.6 m) to September (below –1 m in drained peatlands), reflecting increasing fire susceptibility. Coastal areas maintained higher GWL, likely due to seawater intrusion.

Table 6: Accuracy assessment of land use classification by trajectory data

Class	NoCh	De	Cu	Ur	LanDeg	Re	Total	UA	PA
NoCh	375	1	1	0	0	0	377	99.47	98.94
De	3	28	0	0	0	0	31	90.32	96.55
Cu	0	0	28	0	2	0	30	93.33	96.55
Ur	0	0	0	1	0	0	1	100.00	100.00
LanDeg	1	0	0	0	6	1	8	75.00	75.00
Re	0	0	0	0	0	3	3	100.00	75.00
Total	379	29	29	1	8	4	450		
Overall Accuracy		98.00							
Kappa Coefficient		0.93							

Description: no change (NoCh), deforestation (De), cultivation (Cu), urbanization (Ur), land degradation (LanDeg), reforestation (Re), Producer's Accuracy (PA), and User's Accuracy (UA)

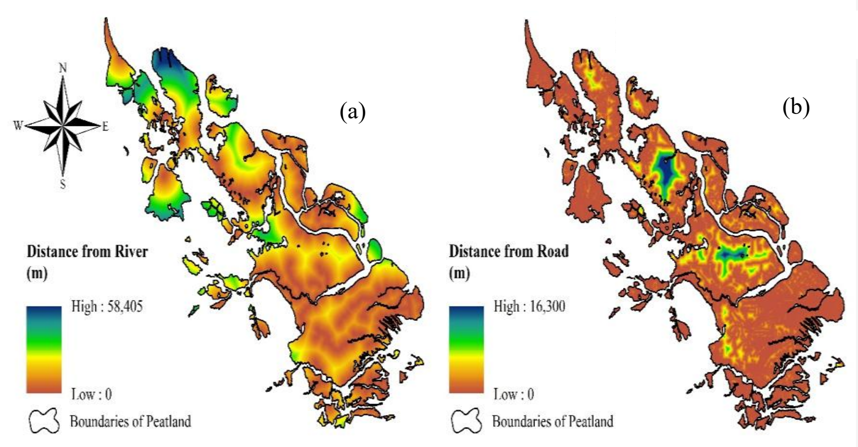

Figure 5: Conditions of (a) distance from river, and (b) distance from road

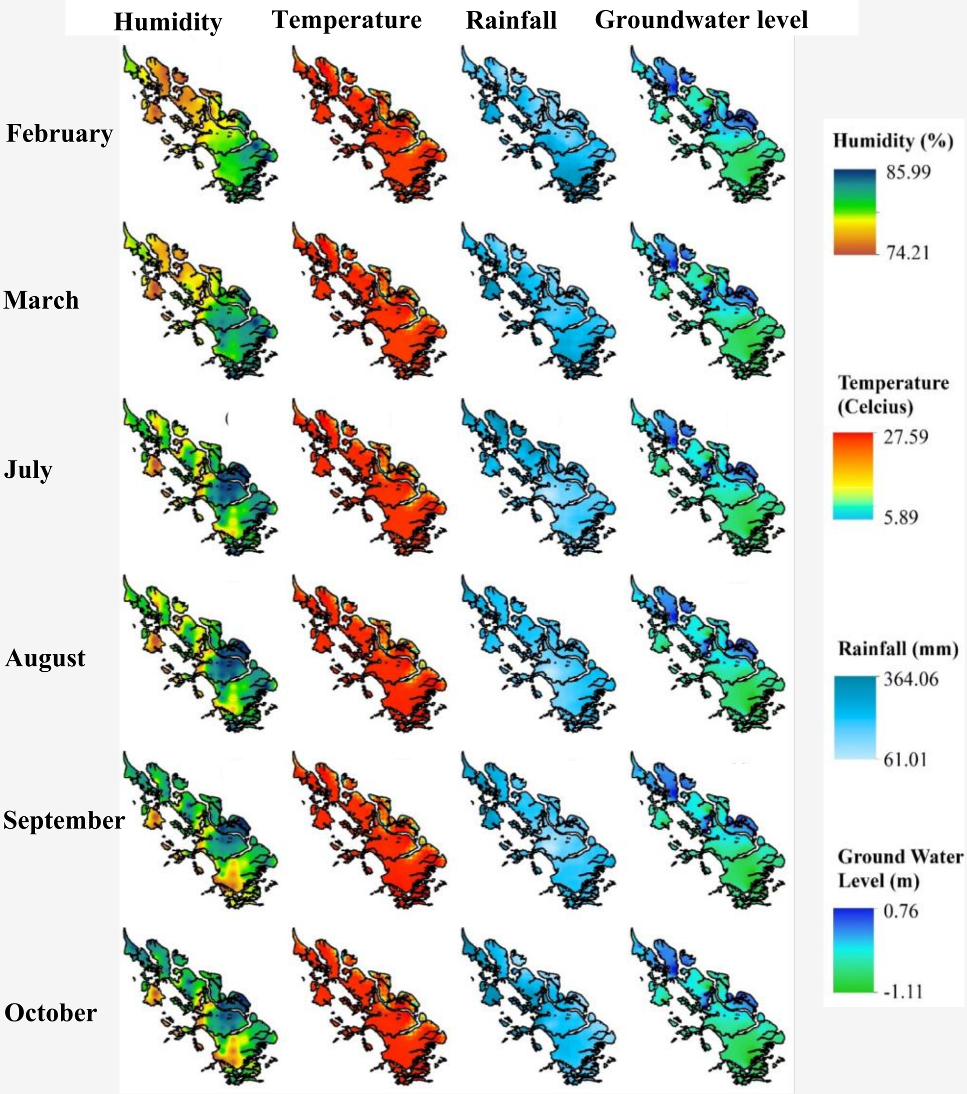

Figure 6: Humidity, temperature, rainfall, ground water level conditions in 2019-2023

During the analysis of climatological data, very low temperatures (approximately 6 °C) were detected in certain grid cells over parts of the islands. This anomaly is not representative of actual near-surface temperatures in the lowland peatlands of Riau but is likely associated with the coarse resolution of ECMWF reanalysis data (0.25°), which averages climatic conditions across large grid cells that include high-elevation areas. In mountainous regions, particularly along the Barisan mountain range in western Sumatra, nighttime radiative cooling and orographic effects can result in substantially lower surface temperatures compared to surrounding lowlands. Additionally, extreme rainfall events followed by radiative cooling may also contribute to transient low values in the dataset. Therefore, the occurrence of ~6 °C temperatures should be interpreted as a localized data artifact or topographic effect rather than a reflection of the general climatic conditions of Riau's peatland ecosystems.

3.2.3 Multicollinearity and variable interactions

Interpreting Random Forest variable importance requires cautious consideration of multicollinearity and complex interactions, which are prevalent in environmental systems (e.g., rainfall, humidity, and GWL; LULCC and spatial proximity). The Pearson correlation analysis (Appendix 1) confirmed substantial collinearity, showing, for instance, strong negative correlations between GWL and both rainfall (r = –0.56 in February; r = –0.45 in March) and humidity (r ≈ –0.47), as well as moderate positive correlations between rainfall and distance from rivers (r = 0.42 in July; r = 0.33 in September). While Random Forest models are robust to multicollinearity in terms of predictive accuracy, such correlations can dilute individual variable importance by distributing explanatory power across predictors and implicitly capturing interactive effects (e.g., GWL's amplified impact when combined with low humidity and high temperature) [60]. This provides insight into LULCC's consistently low individual importance (<1%), as its contribution is likely absorbed by correlated hydrological (GWL, rainfall) and spatial variables (distance to river and road) that also reflect anthropogenic activities. Thus, LULCC's role as a fire driver may be underrepresented in the importance scores, not because it is unimportant, but because its influence overlaps with stronger climatic and hydrological dynamics within the relatively short analysis period.

3.2.4 Prediction of peatland fire susceptibility based on machine learning

3.2.4.1 Variable importance

The variation in variable importance values across different months, reflecting the changing influence of environmental and anthropogenic factors on peatland fire susceptibility, is shown in Table 7. In the FBCR model, importance values are derived from the degree to which each variable reduces prediction error during tree splits. Higher values indicate a stronger role in explaining fire occurrence for a given month, while lower values suggest a weaker contribution. To facilitate interpretation, these raw values are also expressed as percentages, showing the relative contribution of each factor. Such differences, even when large for the same variable across months, highlight the dynamic nature of fire drivers, where climatic and hydrological conditions vary seasonally and alter the relative significance of each predictor in shaping fire patterns. The results of the analysis indicate that hydrological factors, particularly the Ground Water Level (GWL), play a dominant role in determining the pattern of peatland fire occurrence. GWL exhibited the highest variable importance in nearly all months of observation, with significant values recorded in February (17.37%) and March (17.85%). This correlation suggests that a lower water table increases the likelihood of peatland fires, as a reduced water table decreases the moisture content in the peat layer, making it more prone to ignition when exposed to a fire source. Previous studies have demonstrated that a decline in GWL below 40 cm from the ground surface can elevate the likelihood of fire by 70-80% due to the drying of natural fuels in the peat ecosystem [61].

Table 7: Variable importance in the observation time period

Variables	**February**		**March**		**July**		**August**		**September**		**October**	
	Imp	**%**	**Imp**	**%**	**Imp**	**%**	**Imp**	**%**	**Imp**	**%**	**Imp**	**%**
GWL	98.93	17.37	222.54	17.85	55.39	16.98	169.22	16.85	249.54	16.54	27.26	16.52
DfRo	97.44	17.11	210.43	16.88	56.23	16.22	159.11	15.84	238.11	15.78	25.89	15.69
DfRi	97.33	17.09	213.14	17.10	59.87	16.27	172.29	17.15	255.78	16.95	25.92	15.71
Rf	92.72	16.28	201.14	16.13	59.84	17.26	169.10	16.84	267.41	17.72	28.24	17.12
Hm	90.92	15.97	198.38	15.91	57.65	16.63	163.39	16.27	247.83	16.43	26.05	15.79
Tp	90.10	15.82	199.17	15.97	55.98	16.15	169.10	16.84	247.97	16.44	30.32	18.38
LULCC	2.02	0.35	2.02	0.16	1.73	0.50	2.17	0.22	2.13	0.14	1.30	0.79

Additionally, climatic factors play a crucial role in influencing peat fire dynamics, particularly rainfall (Rf), temperature (Tp), and humidity (Hm). Rainfall emerged as the most influential factor in September (17.72%) and October (17.12%), suggesting that increased precipitation reduces fire risk by enhancing ture and organic fuel content. Rainfall anomalies lower than the annual average are frequently associated with heightened fire intensity in Southeast Asian peatlands [62]. However, air temperature also exhibited considerable influence, particularly in October (18.38%). This suggests that rising temperatures are closely associated with an increased frequency of peatland fires. Elevated temperatures accelerate water evaporation from soil and vegetation, thereby enhancing the dryness and flammability of natural fuels [63]. Rising temperatures also contribute to the release of methane gas from degraded peatlands, which exacerbates the impacts of climate change [64].

Furthermore, the influence of air humidity (Hm) was relatively lower than other factors, with importance values ranging from 15.79% to 16.63% across the observation months. However, the consistent influence of air humidity underscores its role in regulating peat fire occurrence. Higher atmospheric humidity can impede fire spread by increasing the moisture content of natural fuels, such as litter and dry twigs, thereby reducing their susceptibility to ignition and intense combustion [65]. While the direct individual contribution of LULCC appeared low, the interplay between LULCC-driven changes and DfRo/DfRi are crucial. The conversion of peatlands into large-scale plantations or agricultural land can lead to the degradation of peat ecosystems, alter hydrological properties, and heighten the risk of future fires [56]. The relatively low importance of land use change in the model is influenced by the limited analysis period (2019–2023), generalized trajectory classification, and the stronger influence of climatic and hydrological variables, such as temperature, rainfall, and groundwater level, which directly affect fire susceptibility. Multicollinearity with these predictors and the seasonal nature of extreme dry periods further weaken the distinct signal of land use change.

In addition to hydrological and climatic factors, spatial variables such as proximity to roads (DfRo) and distance from rivers (DfRi) also exhibit significant contributions to fire occurrence patterns. The distance from roads consistently showed importance values ranging from 15.69% to 17.11%, confirming that access to fire-prone areas is an important factor. Several studies in tropical regions have identified that peatland fires are more likely to occur in areas closer to road networks, due to increased human activities, such as land clearing or illegal burning for agricultural purposes. Finally, the distance from rivers showed a greater influence in March (16.13%) and August (17.15%), indicating that areas farther from water bodies tend to be drier and more susceptible to fire. The absence of natural water sources near fire-prone areas hinders suppression efforts and increases the likelihood of rapid fire spread. This finding aligns with previous research on peatland fires, which indicates that peatlands located farther from natural hydrological systems have higher fire rates than those connected to water networks [66] and [67].

3.2.4.2 Peatland fire susceptibility map

In an effort to understand peatland fire dynamics, machine learning-based modeling was employed to predict peatland fire patterns in Riau Province, Indonesia. The predictions are based on various environmental factors, including meteorological and anthropogenic parameters that contribute to fire occurrence. The primary objective of the analysis is to identify the temporal and spatial patterns of fires and to evaluate the model's performance in predicting areas at high risk of fire. The results indicate that peatland fires in this region are closely associated with the dry season and human activities.

Monthly peatland fire prediction maps reveal that fires tend to accumulate in specific areas, with increasing intensity during the peak months of the dry season (Figure 7). July and August are the periods with the most extensive fires, particularly in central and southern Riau. This trend aligns with findings from previous research, which suggest that peat fires in tropical regions are strongly influenced by the dry season and human activities, such as land clearing by burning [68] and [69]. During these months, extremely low rainfall causes peatlands to dry out more rapidly, thereby increasing their flammability. In contrast, fire intensity is significantly lower in October and February, as increased rainfall enhances soil moisture and reduces the likelihood of fire spread. However, fire hotspots remain in these months, likely due to human activities, including illegal land clearing or negligence in forest management.

The spatial autocorrelation analysis of fire predictions further confirms the presence of clustering patterns in several months, particularly in February, March, July, September, and October. In February, the Moran's I value of 0.138 with a significant p-value ($p = 0.000$) indicates a strong clustering pattern, suggesting that fires are not randomly distributed but rather influenced by spatially correlated factors such as land cover and peat moisture levels.

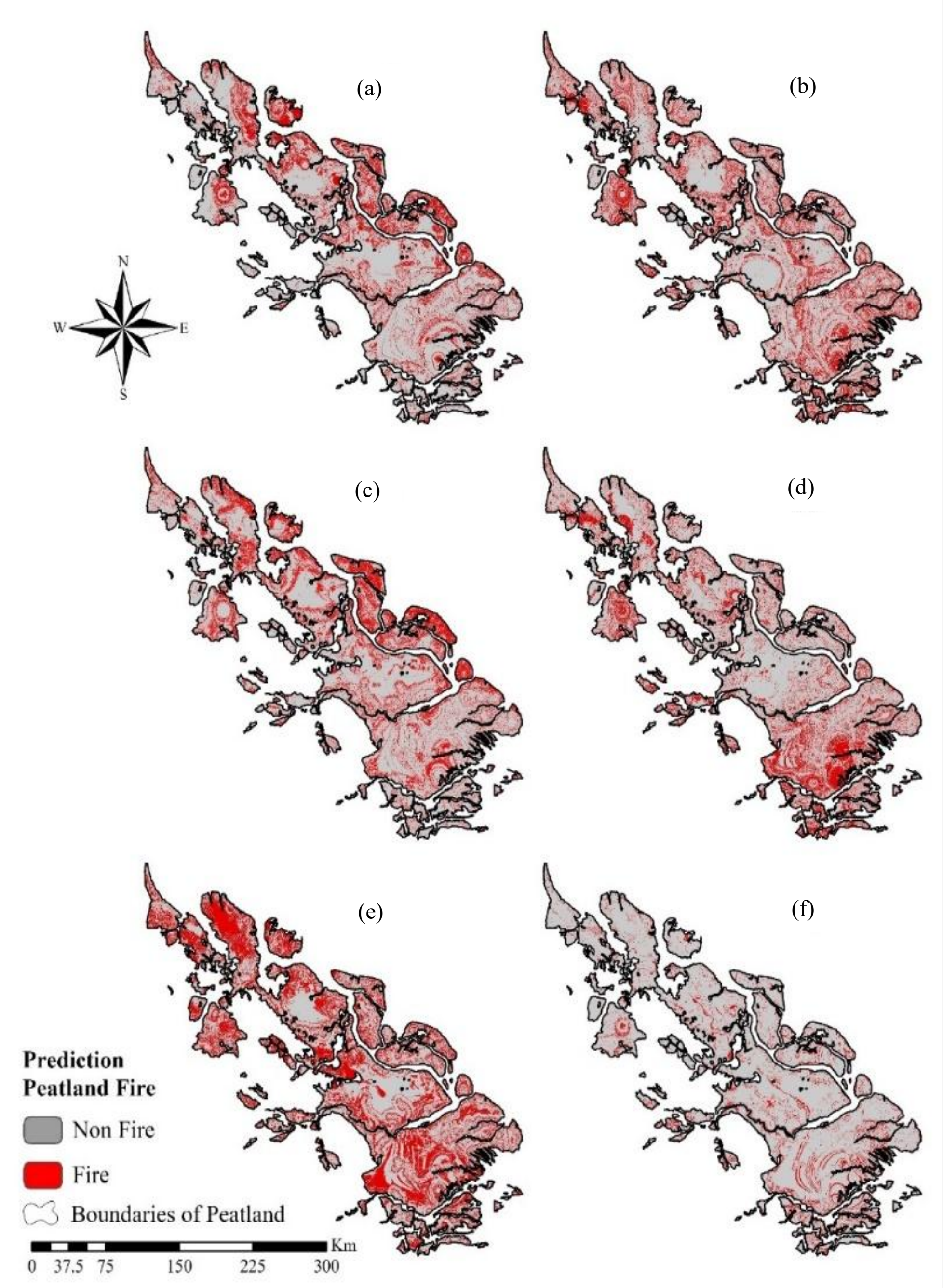

Figure 7: Peatland fire predictions for (a) February, (b) March, (c) July, (d) August, (e) September, and (f) October

This pattern is likely driven by residual dry conditions from the preceding dry season, where fire-prone areas remain susceptible to ignition despite increased precipitation. Similarly, March exhibits a comparable clustering trend (Moran's I = 0.121), further reinforcing the notion that fire-prone regions maintain spatial dependency. Potentially due to lingering human-induced ignitions in degraded peatlands. In contrast, August displays a Moran’s I value of 0.175 with a higher p-value, suggesting that fire distribution in this month does not exhibit significant spatial clustering. This irregularity implies a more dispersed fire pattern, likely influenced by variable peat moisture levels and localized fire suppression efforts.

The randomness of fire occurrences in August might also be attributed to increased monitoring and enforcement activities during peak fire season, leading to a more scattered fire distribution rather than concentrated clusters [70]. Furthermore, July, September, and October maintain positive but lower Moran's I values (0.078, 0.075, and 0.055, respectively), signifying moderate clustering patterns. The clustering observed in these months suggests that fire recurrence is influenced by historical land use patterns, particularly in plantation areas with extensive drainage networks. Additionally, the spatial persistence of fires in September and October may reflect the cumulative impact of prolonged dry conditions and human activities, reinforcing the necessity of targeted fire prevention strategies in high-risk zones.

The fire distribution map reveals that peatland fires are more prevalent in plantation and industrial timber plantation areas compared to other land use types. Areas dominated by oil palm plantations and acacia plantations, represented under the crop category, experienced the most extensive fires, particularly in the southern and central parts of Riau. This suggests that the conversion of peatlands to plantations and pulpwood plantations increases their susceptibility to fires, primarily due to drainage systems that dehydrate the land and facilitate fire ignition [71]. Furthermore, peatlands that have been degraded by human activities tend to be more vulnerable to fire than those that remain intact. Primary and secondary forest areas experience relatively fewer fires, suggesting that human intervention is a major factor contributing to fire occurrence. Therefore, more sustainable land management practices, such as hydrological restoration and the cessation of land clearing by burning, are urgently required to mitigate the risk of future peat fires [72].

The predicted fire-affected area reveals that the largest fire events occurred in July (39.31%) and August (26.12%), while the smallest occurred in October (10.47%). These findings suggest that more than 60% of total fire incidents occurred in these two months of the dry season (Figure 8). Climatological factors play a crucial role in peatland fire dynamics in tropical regions [73]. Additionally, fluctuations in fire extent across the months of observation indicate that, despite seasonal trends, local factors such as peat drainage, deforestation, and human intervention also contribute significantly to fire spread. Areas with dense drainage canal networks tend to experience more extensive fires, as these systems over-drain peat and increase the likelihood of fire ignition [74]. Therefore, strategies based on peatland rewetting can be effective in reducing the risk of future peat fires.

3.2.4.3 Accuracy of peatland fire susceptibility map

An evaluation of the Forest-Based Classification and Regression (FBCR) model was conducted to assess its performance in predicting peatland fire occurrences. Two primary metrics, F1-score and accuracy, were used to evaluate the model on both training and validation datasets over several months within the study period. Overall, the model performed reasonably well, with variations depending on the month and environmental conditions. On the training data, the model achieved exceptionally high accuracy (99%–100%), indicating its strong ability to recognize patterns (Table 8). However, this also suggests the potential for overfitting, a well-documented challenge in high-resolution spatial environmental modeling where complex variable interactions and spatial autocorrelation can reduce generalization performance [10]. Given the notable gap between training and validation accuracy, the issue of overfitting warrants further examination to understand its causes and identify possible remedies.

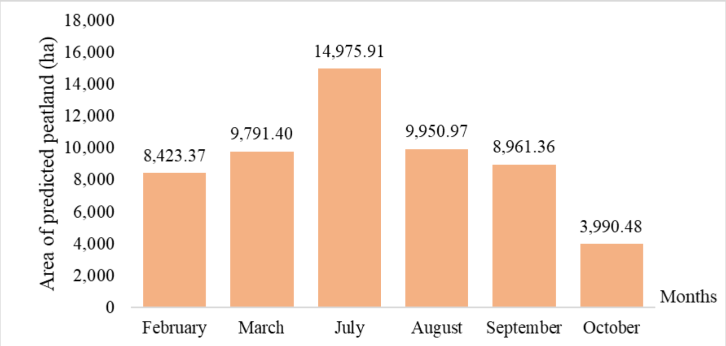

Figure 8: Area of predicted peatland fires during the observation period

Table 8: Model evaluation from training data for the entire observation period

Month	F-1 Score		Accuracy	
	Fire	Non Fire	Fire	Non Fire
February	1.00	1.00	1.00	1.00
March	1.00	1.00	1.00	1.00
July	0.99	0.99	0.99	0.99
August	0.99	1.00	0.99	0.99
September	0.99	0.99	0.99	0.99
October	1.00	1.00	1.00	1.00

Table 9: Model evaluation from validation data for the entire observation period

Month	F-1 Score		Accuracy	
	Fire	Non Fire	Fire	Non Fire
February	0.76	0.76	0.76	0.76
March	0.71	0.72	0.71	0.71
July	0.67	0.66	0.66	0.66
August	0.66	0.73	0.70	0.70
September	0.74	0.74	0.74	0.74
October	0.60	0.83	0.77	0.77

The substantial discrepancy between the training accuracy (99–100%) and validation accuracy (60–76%) suggests that the models may have experienced overfitting. Overfitting occurs when a model captures noise and highly specific patterns in the training dataset, thereby reducing its generalization capability when applied to new or unseen data. In the context of peatland fire prediction, this may be attributed to several factors, including the limited temporal span of the dataset, imbalanced distribution of fire and non-fire samples, and the complex spatial heterogeneity of peatland environments. Although measures such as spatial buffering were employed to reduce autocorrelation, the persistence of overfitting indicates that further refinements are necessary. Similar issues have been reported in wildfire studies, where overfitting was mitigated through data balancing (e.g., SMOTE), regularization, and hyperparameter tuning [75]. Potential remedies include the application of cross-validation strategies, the use of regularization techniques, feature selection to reduce dimensionality, and the incorporation of a larger temporal dataset to better capture variability.

Additionally, ensemble approaches and hyperparameter optimization may improve generalization, thereby enhancing predictive reliability across diverse climatic and land use conditions. When tested on validation data, the model's performance declined slightly, with F1-score values ranging from 60% to 76% (Table 9). Additionally, the model exhibited higher accuracy in February and October (76% and 77%) compared to July and August (66% and 70%). This variation may indicate that fire patterns in certain months align more consistently with the training data, whereas other months involve more complex environmental factors that the model struggles to capture. While FBCR helps reduce overfitting compared to single decision trees, the large number of predictors may still limit generalization. Future work could address this by refining the feature set, optimizing tree parameters, applying spatial cross-validation, and expanding the diversity of training samples where the model becomes overly specialized to the training data, reducing its effectiveness in predicting new data [76].

The advantage of using Forest-based Classification and Regression (FBCR) in this study lies in its ability to directly integrate spatial data with raster/pixel-based data. This model facilitates more accurate geographic and GIS-based analysis compared to conventional classification methods, as FBCR can handle spatial data without the need for additional conversion [77]. Its capacity to manage multiple spatial data formats makes it well-suited for peatland fire studies that require risk map-based analyses. FBCR was specifically chosen for its ability to generate spatial predictions directly within ArcGIS Pro, allowing the creation of peatland fire risk maps that not only show burned or unburned areas but also provide spatial insights into the likelihood of fire occurrence. This capability is particularly valuable for disaster management and mitigation planning, where understanding the spatial distribution of fires can inform the development of more effective policies [78]. Moreover, FBCR can capture the complex relationships between environmental and anthropogenic variables more effectively than linear regression models or simple decision tree algorithms, which often struggle to handle the spatial heterogeneity of the data [79]. Additionally, the use of FBCR in this study not only enhanced prediction accuracy but also provided greater flexibility in the visualization and interpretation of results. The model's ability to incorporate multi-source data simultaneously makes it an invaluable tool for peatland fire risk analysis. Thus, the application of FBCR in this study provides a foundation for the development of more advanced prediction systems in the future, incorporating real-time data and modeling long-term fire scenarios. The findings of this study have significant implications for peatland fire risk management. One key implication is the need to develop a data-driven early warning system to identify high-risk areas before the peak of the dry season.

With machine learning-based predictions, relevant authorities can implement more-timely and evidence-based mitigation measures [80]. Furthermore, rewetting strategies through hydrological restoration should be prioritized in mitigation efforts, particularly in areas with active drainage systems, which are more vulnerable to fires [81]. The model also demonstrates that while machine learning can effectively predict fire patterns, further optimization is necessary to improve its accuracy and generalizability [82]. This includes incorporating additional parameters such as real-time weather data and anthropogenic factors. While the Forest-based Classification and Regression (FBCR) model has been widely recognized in GIS-based environmental modeling, its application to peatland fire susceptibility mapping remains limited in the literature. Most previous studies have relied on more common ensemble methods such as Random Forest or Gradient Boosted Trees, which share conceptual similarities with FBCR in their ability to capture non-linear relationships and quantify variable importance [83]. Compared to these models, FBCR offers additional integration with spatial datasets, allowing simultaneous processing of raster and vector variables within a GIS environment, which is particularly advantageous for peatland ecosystems with complex environmental drivers. However, similar to other tree-based ensemble methods, FBCR can require higher computational resources and may be less interpretable than simpler statistical approaches [76]. This limited yet promising track record underscores the novelty of its application in this study and its potential for broader use in spatial fire risk assessment.

An integrated interpretation of the findings highlights the interconnectedness of ecological, methodological, and policy dimensions in addressing peatland fire risk. Ecologically, the results reaffirm that fire dynamics in peatland ecosystems are strongly influenced by hydrological conditions, land-use practices, and seasonal climatic variability, underscoring the importance of ecosystem-based management. From a methodological perspective, the application of the Forest-Based Classification and Regression (FBCR) model demonstrates the capability of GIS-based machine learning to capture complex spatial relationships, although issues such as overfitting and computational demands indicate areas that require further refinement. These methodological insights have direct policy relevance, as robust modeling outputs can strengthen early warning systems and guide the prioritization of rewetting and restoration programs in high-risk areas, while the recognition of model uncertainties emphasizes the need for adaptive and evidence-based decision-making. By linking ecological drivers, methodological strengths and limitations, and practical management implications, this study offers a holistic foundation for improving fire governance in peatland landscapes.

4. Conclusion

This study applied the Forest-Based Classification and Regression (FBCR) approach to generate peatland fire susceptibility maps in Riau Province by integrating climatic, hydrological, and anthropogenic factors. The findings highlight the dominant role of groundwater level and rainfall, along with temperature, humidity, and accessibility variables, in shaping fire risk. The results demonstrate the capacity of FBCR to handle complex spatial data and provide interpretable outputs that reveal key drivers of peatland fire dynamics. Beyond methodological contributions, the susceptibility maps produced in this study offer practical value for peatland management and fire prevention. They can be used to identify high-risk zones, guide targeted monitoring and resource allocation, and strengthen early warning systems by supporting proactive interventions before severe fire events occur. These insights directly contribute to data driven policies for mitigating fire hazards while promoting sustainable land use and peatland conservation. This study highlights the strength of FBCR in capturing nonlinear interactions and improving the reliability of fire susceptibility mapping. While LST was not used here, its integration in future studies could refine hotspot detection and enhance data-driven fire management.

5. Limitations and Future Research

Although the model used in this study has demonstrated reasonable accuracy in predicting peatland fires, several limitations must be considered. One of the primary limitations is the potential for overfitting, where the model performs exceptionally well on training data but experiences a decline in accuracy when tested with new data. This issue suggests that while FBCR exhibits strong classification capabilities, enhanced validation methods and more optimal feature selection are required to improve the model's generalizability. Additionally, the model relies on historical data and does not incorporate real-time weather conditions or dynamic anthropogenic factors. Future research should focus on developing ensemble learning or deep learning-based models to enhance prediction accuracy. Integration with high-resolution remote sensing technology and drone-based monitoring systems could further improve the model's ability to detect fire-prone areas. Furthermore, incorporating additional environmental variables, such as drought indices, soil moisture levels, or long-term rainfall patterns, may further enhance predictive accuracy.

Moreover, certain approaches used in this study did not fully account for spatial dependencies, which are crucial in geospatial-based studies. The spatial distribution of peatland fires is influenced by various geographic and environmental factors, and a more spatially explicit approach could enhance prediction accuracy.

Future research could integrate spatial dependence directly into the modeling process through methods such as spatial lag models or geographically weighted regression (GWR) to account for localized variations in fire susceptibility. Advanced approaches, including deep learning or hybrid spatial statistical frameworks combined with FBCR, could further enhance the model's ability to capture complex spatial patterns and nonlinear mitigation strategies. relationships. These techniques could be incorporated into the workflow after the variable processing stage, ensuring that both environmental predictors and their spatial autocorrelation are explicitly addressed. Moreover, Extend the temporal range of land use data, employ more detailed classification schemes, and integrate higher-frequency observations to better capture its role in peat fire dynamics. Additionally, overfitting can be mitigated through techniques such as cross-validation and model regularization, which would improve the robustness and generalizability of the model. In addition, incorporating social, economic, and policy related variables such as population density, land management practices, and fire prevention policies would provide a more comprehensive understanding of human-driven fire dynamics and strengthen the model's relevance for targeted.

Another critical aspect that requires further exploration is the influence of hydrological infrastructure, particularly the proximity to drainage canals, on peatland fire occurrence. Drainage canals significantly alter the hydrological balance of peatland ecosystems, leading to increased peat dryness and higher fire susceptibility. While this study considers several hydrological and land-use/land cover factors, the specific impact of distance from drainage canals on fire risk has not been explicitly analyzed. Future studies should integrate high-resolution hydrological data and spatial modeling techniques to assess the relationship between canal proximity and peatland fire frequency. This would provide deeper insights into how water management practices influence fire dynamics and offer evidence-based recommendations for sustainable peatland restoration and fire prevention strategies.

By addressing these limitations, future research can make significant contributions to more effective, data-driven peatland fire management and mitigation. The integration of spatially explicit modeling approaches with multi-temporal data and advanced analytical techniques will provide deeper insights into peatland fire dynamics and the effectiveness of mitigation policies.

Acknowledgment

This research was supported by the College of Computing, Khon Kaen University, through the ASEAN GMS Scholarship. The authors would like to express their gratitude to the College of Computing for providing access to ArcGIS Pro licenses, which were essential for the spatial analysis in this study. Additionally, sincere appreciation is extended to the ASEAN GMS Scholarship for the financial support that enabled the completion of this research. The authors also thank the academic institutions that provided scholarships and the government agencies in Indonesia for their assistance in supplying relevant data.

References

[1] Renou-Wilson, F., Moser, G., Fallon, D., Farrell, C.A., Müller, C. and Wilson, D., (2019). Rewetting Degraded Peatlands for Climate and Biodiversity Benefits: Results from Two Raised Bogs. *Ecological Engineering,* Vol. 127; 547–560. https://doi.org/10.1016/j.ecoleng.2018.02.014.

[2] Ribeiro, K., Pacheco, F. S., Ferreira, J. W., de Sousa-Neto, E. R., Hastie, A., Krieger Filho, G. C., Alvalá, P. C., Maria C Forti, M, C. and Ometto, J. P., (2021). Tropical Peatlands and their Contribution to the Global Carbon Cycle and Climate Change. *Global Change Biology*, Vol. 27; 489–505. https://doi.org/10.1111/gcb.15408.

[3] Bourgeau-Chavez, L. L., Grelik, S. L., Billmire, M., Jenkins, L. K., Kasischke, E. S. and Turetsky, M. R., (2020). Assessing Boreal Peat Fire Severity and Vulnerability of Peatlands to Early Season Wildland Fire. Frontiers in Forests and Global Change, Vol. 3; 1–13. https://doi.org/10.3389/ffgc.2020.00020.

[4] Taufik, M., Haikal, M., Widyastuti, M.T., Arif, C. and Santikayasa, I. P., (2023). The Impact of Rewetting Peatland on Fire Hazard in Riau, Indonesia. *Sustainability,* Vol. 15. https://doi.org/10.3390/su15032169.

[5] Rossita, A., Boer, R., Hein, L., Nurrochmat, D. R. and Riqqi, A., (2023). Peatland Fire Regime Across Riau Peat Hydrological Unit, Indonesia. *Forest and Society*, Vol. 7; 76–94. http://doi.org/10.24259/fs.v7i1.21996.

[6] Morison, M. Q., Petrone, R. M., Wilkinson, S. L., Green, A. and Waddington, J. M., (2020). Ecosystem Scale Evapotranspiration and CO_2 Exchange in Burned and Unburned Peatlands: Implications for the Ecohydrological Resilience of Carbon Stocks to Wildfire. *Ecohydrology,* Vol. 13(2). https://doi.org/10.1002/eco.2189.

[7] Forest Fires Seared through 30,477 Thousand Hectares Area in July. *Antara News*. [Online], Available: https://en.antaranews.com/news/128988/forest-fires-seared-through-30477-thousand-hectares-area-in-july [Accessed: Jun. 20, 2025].

[8] Lokasi Karhutla Riau Dalam 5 Tahun Terakhir [Locations of Forest and Land Fires in Riau in the Last 5 Years]. *Tempo*. [Online], Available: https://www.tempo.co/lingkungan/-lokasi-karhutla-riau-dalam-5-tahun-terakhir-2051951 [Accessed: Jun. 20, 2025].

[9] Ramadhi, A., Prakoso, A., Perdana, W. A. and Amukti, R., (2023). Unveiling Forest and Land Fires Vulnerability in the Peat Hydrological Unity Area (PHU) in 2023. [Online], Available: https://pantaugambut.id/storage/widget_multiple/eng-laporan-kerentanan-karhutla-2023-compressed-KeKp0.pdf [Accessed: Jun. 21, 2025].

10] Hayasaka, H., (2023). Peatland Fire Weather Conditions in Sumatra, Indonesia. *Climate,* Vol. 11. https://doi.org/10.3390/cli11050092.

[11] Prasetyo, L.B., Setiawan, Y., Condro, A.A., Kustiyo, K., Putra, E.I., Hayati, N., Wijayanto, A.K., Ramadhi, A., Murdiyarso, D. (2022). Assessing Sumatran Peat Vulnerability to Fire Under Various Conditions of ENSO Phases Using Machine Learning Approaches. *Forests,* Vol. 13(6). https://doi.org/10.3390/f13060828.

[12] Syaufina, L. and Hamzah, A. A., (2021). Changes of Tree Species Diversity in Peatland Impacted by Moderate Fire Severity at Teluk Meranti, Pelalawan, Riau Province, Indonesia. *Biodiversitas,* Vol. 22; 2899–2908. https://doi.org/10.13057/biodiv/d220555.

[13] Wooster, M. J., Gaveau, D. L. A., Salim, M. A., Zhang, T., Xu, W., Green, D. C., Huijnen, V., Murdiyarso, D., Gunawan, D., Borchard, N., Schirrmann, M., Main, B. and Sepriando, A., (2018). New Tropical Peatland Gas and Particulate Emissions Factors Indicate 2015 Indonesian Fires Released Far More Particulate Matter (but Less Methane) Than Current Inventories Imply. *Remote Sensing*, Vol. 10; 1–31. https://doi:10.3390/rs10040495.

[14] Graham, L. L. B., Applegate, G. B., Thomas, A., Ryan, K. C., Saharjo, B. H. and Cochrane, M. A., (2022). A Field Study of Tropical Peat Fire Behaviour and Associated Carbon Emissions. *Fire*, Vol. 5; 1–20. https://doi.org/10.1016/j.scitotenv.2019.134199.

[15] Rossita, A., Boer, R., Hein, L. and Nurrochmat, D. R., (2023). Peatland Fire Regime across Riau Peat Hydrological Unit, Indonesia. *Forest and Society*, Vol. 7(1); 76-94. https://doi.org/10.242 59/fs.v7i1.21996.

[16] Sinclair, A. L., Graham, L. L. B., Putra, E. I., Saharjo, B. H., Applegate, G., Grover, S. P. and Cochrane, M. A., (2020). Effects of Distance from Canal and Degradation History on Peat Bulk Density in a Degraded Tropical Peatland. *Science of the Total Environment,* Vol. 699. https://doi.org/10.1016/j.scitotenv.2019.134199.

[17] Dhandapani, S. and Evers, S., (2020). Oil Palm 'Slash-and-Burn' Practice Increases Post-Fire Greenhouse Gas Emissions and Nutrient Concentrations in Burnt Regions of an Agricultural Tropical Peatland. *Science of the Total Environment*, Vol. 742. https://doi.org/10.1016/j.scitotenv.2020.140648.

[18] Rodríguez Vásquez, M. J., Benoist, A., Roda, J. M. and Fortin, M., (2021). Estimating Greenhouse Gas Emissions from Peat Combustion in Wildfires on Indonesian Peatlands, and Their Uncertainty. *Global Biogeochemical Cycles*, Vol. 35; 1–17. https://doi.org/10.1029/2019GB006218.

[19] Verstegen, J. A., van der Laan, C., Dekker, S. C., Faaij, A. P. C. and Santos, M. J., (2019). Recent and Projected Impacts of Land Use and Land Cover Changes on Carbon Stocks and Biodiversity in East Kalimantan, Indonesia. *Ecological Indicators*, Vol. 103; 563–575. https://doi.org/10.1016/j.ecolind.2019.04.053.

[20] Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S. and Flannigan, M. D., (2020). A Review of Machine Learning Applications in Wildfire Science and Management. *Environmental Reviews*, Vol. 28; 478–505. https://doi.org/10.1139/er-2020-0019

[21] Lai, X., Tang, X., Ren, Z., Li, Y., Huang, R., Chen, J. and You, H., (2024). Study on the Influencing Factors of Forest Tree-Species Classification Based on Landsat and Sentinel-2 Imagery. *Forests*, Vol. 15. https://doi.org/10.3390/f15091511.

[22] Eslami, R., Azarnoush, M., Kialashki, A. and Kazemzadeh, F., (2021). GIS-Based Forest Fire Susceptibility Assessment by Random Forest, Artificial Neural Network and Logistic Regression Methods. *Journal of Tropical Forest Science*, Vol. 33; 173–184. https://doi.org/10.26525/jtfs2021.33.2.173.

[23] Turetsky, M. R., Benscoter, B., Page, S., Rein, G. and van der Werf, G. R., (2015). Controls on Global Peat Fires and Consequences for the Carbon Cycle. *Nature Geoscience*, Vol. 8; 1–23. https://doi.org/10.1038/ngeo2325.

[24] Wang, C., Liu, H., Xu, Y. and Zhang, F., (2025). A Forest Fire Prediction Framework Based on Multiple Machine Learning Models. *Forests*, Vol 16; 1–17. https://doi.org/10.3390/f16020329.

[25] Haryanto, R., Juandi, Siregar, S. and Suwondo., (2023). 30 Years Trend of Peatland Utilization in Riau Province. *IOP Conference Series: Earth and Environmental Science*, Vol. 1230. https://doi.org/10.1088/1755-1315/1230/1/012066.

[26] Balling, J., Verbesselt, J., De Sy, V., Herold, M. and Reiche, J., (2021). Exploring Archetypes of Tropical Fire-Related Forest Disturbances Based on Dense Optical and Radar Satellite Data and Active Fire Alerts. *Forests*, Vol. 12. https://doi.org/10.3390/f12040456.

[27] Tan, Z. D., Sutikno, S., Carrasco, L. R., and Taylor, D., (2023). Local Community Representations of Tropical Peatlands and Implications for Restoration in Riau, Indonesia. *Restoration Ecology*, Vol. 31, 1–14. https://doi.org/10.1111/rec.13900.

[28] Marwanto, S., Sabiham, S. and Funakawa, S., (2019). Importance of CO_2 Production in Subsoil Layers of Drained Tropical Peatland under Mature Oil Palm Plantation. *Soil and Tillage Research*, Vol. 186; 206–213. https://doi.org/10.1016/j.still.2018.10.021.

[29] Thorburn, C. C. and Kull, C. A., (2015). Peatlands and Plantations in Sumatra, Indonesia: Complex Realities for Resource Governance, Rural Development and Climate Change Mitigation. *Asia Pacific Viewpoint*, Vol. 56; 153–168. https://doi.org/10.1111/apv.12045.

[30] Krashevska, V., Tsyganov, A. N., Esaulov, A. S., Mazei, Y. A., Hapsari, K. A., Saad, A., Mazei, A. Y., and Mazei, Y., (2020). Testate Amoeba Species- and Trait-Based Transfer Functions for Reconstruction of Hydrological Regime in Tropical Peatland of Central Sumatra, Indonesia. *Frontiers in Ecology and Evolution*, Vol. 8; 1–15. https://doi.org/10.3389/fevo.2020.00225.

[31] Omar, M. S., Ifandi, E., Sukri, R. S., Kalaitzidis, S., Christanis, K., Lai, D. T. C., Kalioras, A., Alexakis, D. and Christanis, K., (2022). Peatlands in Southeast Asia: A Comprehensive Geological Review. *Earth-Science Reviews*, Vol. 232. https://doi.org/10.1016/j.earscirev.2022.104149.

[32] Giofandi, E. A., Syahzaqi, I., Sekarjati, D., Putriana, A. M., Putti, H. M. D. M. and Sekarrini, C. E., (2024). Assessment of Remote Sensing Approach for Urban Ecological Quality Evaluation in Pekanbaru City, Riau Province Indonesia. *Geography, Environment, Sustainability*, Vol. 17; 28–35. https://doi.org/10.24057/2071-9388-2023-2640.

[33] Pribadi, D. O. and Kusuma, Y. W. C., (2015). Microhabitat Influence on Growth Distribution Pattern of Ramin (Gonystylus bancanus) in Siak, Riau Province. *Biotropia*, Vol. 22; 1–10. https://doi.org/10.11598/btb.2015.22.1.284.

[34] ASEAN. (2010). ASEAN Biodiversity Outlook. [Online]. Available: https://www.aseanbiodiversity.org/ [Accessed: Oct. 24, 2025].

[35] Suwondo, Wulandari, S., Darmadi, Haryanto, R. and Ramdani, I., (2023). Dominance of Palm Oil Plantation Utilization on Peatlands in Riau Province. *IOP Conference Series: Earth and Environmental Science*, Vol. 1230. https://doi.org/10.1088/1755-1315/1230/1/012001.

[36] Dinas Lingkungan Hidup dan Kehutanan PPR. (2023). Analisis Isu Lingkungan Hidup Daerah Pengelolaan [Environmental Issue Analysis in Management Areas]. [Online], Available: https://dlhk.ppr.go.id/ [Accessed: Oct. 24, 2025].

[37] Speiser, J. L., Miller, M. E., Tooze, J. and Ip, E., (2019). A Comparison of Random Forest Variable Selection Methods for Classification Prediction Modeling. *Expert Systems with Applications*, Vol. 134; 93–101. https://doi.org/10.1016/j.eswa.2019.05.028.

[38] Zhang, G., Wang, M. and Liu, K., (2019). Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. *International Journal of Disaster Risk Science*, Vol. 10; 386–403. https://doi.org/10.1007/s13753-019-00233-1.

[39] Sekarjati, D., Putklang, W. and Wattanakij, N., (2024). Identifying Peatland Fire Detection and Spatiotemporal Distribution: Implications for Land Use and Land Cover Changes in Riau Province, Indonesia. *International Computer Science and Engineering Conference*, 1–6. https://doi.org/10.1109/ICSEC62781.2024.10770752.

[40] Pan, T., Bao, Z., Ning, L. and Tong, S., (2022). Change of Rice Paddy and Its Impact on Human Well-Being from the Perspective of Land Surface Temperature in the Northeastern Sanjiang Plain of China. *International Journal of Environmental Research and Public Health*, Vol. 19; 1–18. https://doi.org/10.3390/ijerph19159690.

[41] Maialetti, M., Ciaschini, C., Quaranta, G., Salvia, R., Scarpitta, D., Bigiotti, S., Pagano, L. and Salvia, R., (2024). Investigating Land-Use Trajectories in Mediterranean Rural Areas with Official Statistics and a Multiway Factor Analysis. *Sustainability*, Vol. 16. https://doi.org/10.3390/ su16177644.

[42] Abd Ellah, R. G., (2021). Morphometric Analysis of Toshka Lakes in Egypt: A Succinct Review of Geographic Information Systems and Remote Sensing-Based Techniques. *Egyptian Journal of Aquatic Research*, Vol. 47, 215–221. https://doi.org/10.1016/j.ejar.2021.05.005.

[43] Zinzendoff Okwonu, F., Laro Asaju, B. and Irimisose Arunaye, F., (2020). Breakdown Analysis of Pearson Correlation Coefficient and Robust Correlation Methods. *IOP Conference Series: Materials Science and Engineering*, Vol. 917; 1–9. https://doi.org/10.1088/1757-899X/917/1/012065.

[44] Ho, K. T., (1998). The Random Subspace Method for Constructing Decision Forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20; 832–844. https://doi.org/10.1109/34.709601.

[45] Song, J., Wang, Y., Fang, Z., Peng, L. and Hong, H., (2020). Potential of Ensemble Learning to Improve Tree-Based Classifiers for Landslide Susceptibility Mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol 13, 4642–4662. https://doi.org/10.1109/JSTARS.2020.3014143.

[46] Probst, P., Wright, M. N. and Boulesteix, A. L., (2019). Hyperparameters and Tuning Strategies for Random Forest. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, Vol. 9, 1–15. https://doi.org/10.1002/widm.1301.

[47] Gu, Y., Wylie, B. K., Boyte, S. P., Picotte, J., Howard, D. M., Smith, K. and Nelson, K., (2016). An Optimal Sample Data Usage Strategy to Minimize Overfitting and Underfitting Effects in Regression Tree Models Based on Remotely-Sensed Data. *Remote Sensing*, Vol. 8; 20–26. https://doi.org/10.3390/rs8110943.

[48] Farhadpour, S., Warner, T. A., and Maxwell, A. E., (2024). Selecting and Interpreting Multiclass Loss and Accuracy Assessment Metrics for Classifications with Class Imbalance: Guidance and Best Practices. *Remote Sensing,* Vol. 16; 1–22. https://doi.org/10.3390/rs16030533.

[49] Mirza, B., Haroon, D., Khan, B., Padhani, A. and Syed, T. Q., (2021). Deep Generative Models to Counter Class Imbalance: A Model-Metric Mapping with Proportion Calibration Methodology. *IEEE Access*, Vol. 9; 55879–55897. https://doi.org/10.1109/ACCESS.2021.3071389.

[50] Baykal, T. M., (2025). Performance Assessment of GIS-Based Spatial Clustering Methods in Forest Fire Data. *Springer Netherlands*. Vol. 121; 8445-8477. https://doi.org/10.1007/s11069-025-07135-0

[51] Humpenöder, F., Karstens, K., Lotze-Campen, H., Leifeld, J., Menichetti, L., Barthelmes, A., Popp, A., Humpenöder, F. and Leifeld, J., (2020). Peatland Protection and Restoration Are Key for Climate Change Mitigation. *Environmental Research Letters*, Vol. 15; 1–9. https://doi.org/10.1088/1748-9326/abae2a.

[52] Tian, J., Wang, H., Vilgalys, R., Ho, M., Flanagan, N. and Richardson, C. J., (2021). Response of Fungal Communities to Fire in a Subtropical Peatland. *Plant and Soil*, Vol. 466; 525–543. https://doi.org/10.1007/s11104-021-05070-0.

[53] Trihadmojo, B., Jones, C.R., Prasastyoga, B., Walton, C. and Sulaiman, A., (2020). Toward a Nuanced and Targeted Forest and Peat Fires Prevention Policy: Insight from Psychology. *Forest Policy and Economics*, Vol. 120. https://doi.org/10.1016/j.forpol.2020.102293.

[54] Marrs, R. H., Marsland, E. L., Lingard, R., Appleby, P. G., Piliposyan, G. T., Rose, R. J. and Evans, M. G., (2019). Experimental Evidence for Sustained Carbon Sequestration in Fire-Managed, Peat Moorlands. *Nature Geoscience*, Vol. 12,108–112. https://doi.org/10.1038/s41561-018-0266-6.

[55] Miettinen, J., Shi, C. and Liew, S. C., (2017). Fire Distribution in Peninsular Malaysia, Sumatra and Borneo in 2015 with Special Emphasis on Peatland Fires. *Environmental Management*, Vol. 60, 747–757. https://doi.org/10.1007/s00267-017-0911-7.

[56] Arisanty, D., Muhaimin, M., Rosadi, D., Saputra, A. N., Hastuti, K. P. and Rajiani, I., (2021). Spatiotemporal Patterns of Burned Areas Based on the Geographic Information System for Fire Risk Monitoring. *International Journal of Forestry Research*, 11–14. https://doi.org/10.1155/2021/2784474.

[57] Simpson, J. E., Wooster, M. J., Smith, T. E. L., Trivedi, M., Vernimmen, R. E., Dedi, R. and Dharmawan, D., (2016). Tropical Peatland Burn Depth and Combustion Heterogeneity Assessed Using UAV Photogrammetry and Airborne LiDAR. *Remote Sensing*, Vol. 8; 1–15. https://doi.org/10.3390/rs8121000.

[58] Konecny, K., Ballhorn, U., Navratil, P., Jubanski, J., Page, S. E., Tansey, K., Hooijer, A., Vernimmen, R., Miettinen, J. and van der Werf, G. R., (2016). Variable Carbon Losses from Recurrent Fires in Drained Tropical Peatlands. *Global Change Biology*, Vol. 22; 1469–1480. https://doi.org/10.1111/gcb.13186.

[59] Ohkubo, S., Hirano, T. and Kusin, K., (2021). Influence of Fire and Drainage on Evapotranspiration in a Degraded Peat Swamp Forest in Central Kalimantan, Indonesia. *Journal of Hydrology*, Vol. 603. https://doi.org/10.1016/j.jhydrol.2021.126906.

[60] Gregorutti, B., Michel, B. and Saint-Pierre, P., (2017). Correlation and Variable Importance in Random Forests. *Statistics and Computing*, Vol. 27, 659–678. https://doi.org/10.1007/s11222-016-9646-1.

[61] Irfan, M., Koriyanti, E., Saleh, K., Hadi, S., Safrina, S. and Awaludin, A., (2024). Dynamics of Peatland Fires in South Sumatra in 2019: Role of Groundwater Levels. *Land*, Vol. 13; 1–15. https://doi.org/10.3390/land13030373.

[62] Hayasaka, H., Usup, A. and Naito, D., (2020). New Approach Evaluating Peatland Fires in Indonesian Factors. *Remote Sensing*, Vol. 12; 1–14. https://doi.org/10.3390/RS12122055.

[63] Dadap, N. C., Cobb, A. R., Hoyt, A. M., Harvey, C. F., Feldman, A. F. and Im, E. S., (2022). Climate Change-Induced Peatland Drying in Southeast Asia. *Environmental Research Letters*, Vol. 17; 1–13. https://doi.org/10.1088/1748-9326/ac7969.

[64] Gill, A. L., Giasson, M. A., Yu, R. and Finzi, A. C., (2017). Deep Peat Warming Increases Surface Methane and Carbon Dioxide Emissions in a Black Spruce-Dominated Ombrotrophic Bog. *Global Change Biology*, Vol. 23; 5398–5411. https://doi.org/10.1111/gcb.13806.

[65] Huang, X. and Rein, G., (2015). Computational Study of Critical Moisture and Depth of Burn in Peat Fires. *International Journal of Wildland Fire*, Vol. 24; 798–808. https://doi.org/10.1071/WF14178.

[66] Brown, L. E., Holden, J., Palmer, S. M., Johnston, K., Ramchunder, S. J. and Grayson, R., (2015). Effects of Fire on the Hydrology, Biogeochemistry, and Ecology of Peatland River Systems. *Freshwater Science*, Vol. 34; 1406–1425. https://doi.org/10.1086/683426.

[67] Taufik, M., Veldhuizen, A. A., Wösten, J. H. M. and van Lanen, H. A. J., (2019). Exploration of the Importance of Physical Properties of Indonesian Peatlands to Assess Critical Groundwater Table Depths, Associated Drought and Fire Hazard. *Geoderma*, Vol. 347; 160–169. https://doi.org/10.1016/j.geoderma.2019.04.001.

[68] Cole, L. E. S., Bhagwat, S. A. and Willis, K. J., (2019). Fire in the Swamp Forest: Palaeoecological Insights into Natural and Human-Induced Burning in Intact Tropical Peatlands. *Frontiers in Forests and Global Change*, Vol. 2; 1–15. https://doi.org/10.3389/ffgc.2019.00048.

[69] Widyastuti, H., Hartono, and Kurniawan, A., (2020). The Use of OBIA for Extraction of Land Cover and Land Use in the City of Palu. *IOP Conference Series: Earth and Environmental Science*, 1–13. https://doi.org/10.1088/1755-1315/485/1/012053.

[70] Carvalho, R. D. C. F., Moreira, T. R., Souza, K. B. D., Costa, G. A., Zanetti, S. S., Barbosa, K. V. and Ferreira, R. G., (2022). GIS-Based Approach Applied to Study of Seasonal Rainfall Influence Over Flood Vulnerability. *Water (Switzerland)*, Vol. 14; 1–15. https://doi.org/10.3390/w14223731.

[71] Evers, S., Yule, C. M., Padfield, R., O'Reilly, P. and Varkkey, H., (2017). Keep Wetlands Wet: The Myth of Sustainable Development of Tropical Peatlands – Implications for Policies and Management. *Global Change Biology*, Vol. 23; 534–549. https://doi.org/10.1111/gcb.13422.

[72] Syaufina, L. and Hafni, D. A. F., (2018). Variability of Climate and Forest and Peat Fires Occurrences in Bengkalis Regency, Riau. *Jurnal Silvikultur Tropika*, Vol. 9; 60–68. https://doi.org/10.29244/j-siltrop.9.1.60-68.

[73] Harrison, M. E., Ottay, J. B., D'Arcy, L. J., Cheyne, S. M., Anggodo, Belcher, C., Cole, L. E. S., Dohong, A., Erman, A. and Page, S. E., (2020). Tropical Forest and Peatland Conservation in Indonesia: Challenges and Directions. *People and Nature*, Vol. 2; 4–28. https://doi.org/10.1002/pan3.10060.

[74] Horton, A. J., Virkki, V., Lounela, A., Miettinen, J., Alibakhshi, S. and Kummu, M., (2021). Identifying Key Drivers of Peatland Fires Across Kalimantan's Ex-Mega Rice Project Using Machine Learning. *Earth and Space Science*, Vol. 8; 1–17. https://doi.org/10.1029/2021EA001873.

[75] Shmuel, A. and Heifetz, E., (2022). Global Wildfire Susceptibility Mapping Based on Machine Learning Models. *Forests*, Vol. 13; 1–15. https://doi.org/10.3390/f13071050.

[76] De Silva, S. and Taro, U., (2025). A Model for Complementing Landslide Types (Cliff Type) Missing from Areal Disaster Inventories Based on Landslide Conditioning Factors for Earthquake-Proof Regions. *Sustainability*, Vol. 17; 1–14. https://doi.org/10.3390/su17177613.

[77] Collins, L., Griffioen, P., Newell, G. and Mellor, A., (2018). The Utility of Random Forests for Wildfire Severity Mapping. *Remote Sensing of Environment*, Vol. 216; 374–384. https://doi.org/10.1016/j.rse.2018.07.005.

[78] Xu, J., Morris, P. J., Liu, J. and Holden, J., (2018). PEATMAP: Refining Estimates of Global Peatland Distribution Based on a Meta-Analysis. *Catena*, Vol. 160; 134–140. https://doi.org/10.1016/j.catena.2017.09.010.

[79] Fox, E. W., Ver Hoef, J. M. and Olsen, A. R., (2020). Comparing Spatial Regression to Random Forests for Large Environmental Data Sets. *PLoS ONE*, Vol. 15; 1–22. https://doi.org/10.1371/journal.pone.0229509.

[80] Hodges, J. L. and Lattimer, B. Y., (2019). Wildland Fire Spread Modeling Using Convolutional Neural Networks. *Fire Technology*, Vol. 55; 2115–2142. https://doi.org/10.1007/s10694-019-00846-4.

[81] Marwanto, S., Watanabe, T., Iskandar, W. and Sabiham, S., (2018). Effects of Seasonal Rainfall and Water Table Movement on the Soil Solution Composition of Tropical Peatland. *Soil Science and Plant Nutrition*, Vol. 64; 386–395. https://doi.org/10.1080/00380768.2018.1436940.

[82] DeLancey, E. R., Kariyeva, J., Bried, J. T. and Hird, J. N., (2019). Large-Scale Probabilistic Identification of Boreal Peatlands Using Google Earth Engine, Open-Access Satellite Data, and Machine Learning. *PLoS ONE*, Vol. 14; 1–17. https://doi.org/10.1371/journal.pone.0218165.

[83] McClarren, R. G., (2021). Decision Trees and Random Forests for Regression and Classification. In Machine Learning for Engineers. *Springer Nature: Cham, Switzerland*, 55–82. https://doi.org/10.1007/978-3-030-70388-2_3.