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Monitoring of Land Use and Land Cover Changes Based on Machine Learning in Rokan Hilir Peat Hydrological Unit, Riau
(Monitoring Perubahan Tutupan dan Penggunaan Lahan Berbasis Machine Learning di Kesatuan Hidrologis Gambut Rokan Hilir, Riau)

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Abstract

The Peat Hydrological Unit (PHU) of Rokan Hilir Regency is one of the peatland areas in Riau Province experiencing extensive peatland conversion. This conversion can lead to degradation of peat ecosystems and increase the risk of forest and land fires. However, the limited availability of long-term spatial data on land cover and land-use dynamics in the Rokan Hilir PHU remains a major constraint on sustainable peatland management. This study aims to analyze the land cover and land use classes that experienced the most significant changes and to estimate their magnitude during the 2005-2023 period. Land cover and land use classification were conducted using the Random Forest algorithm with 12 indices as input variables. The land cover and land use were classified into six classes: water bodies, built-up, bare land, oil palm plantations, natural forests, and plantation forests. The results showed that during 2005-2023, the largest decreases occurred in natural forest (119,186.3 ha) and plantation forest (72,135.6 ha). Meanwhile, the largest increases were observed in oil palm plantation (146,384.7 ha) and built-up (22,101.2 ha).

Keywords: *Degradation, land use-land cover, peatland, random forest*

Abstrak

Kesatuan Hidrologis Gambut (KHG) Kabupaten Rokan Hilir merupakan salah satu kawasan di Provinsi Riau yang mengalami konversi lahan gambut tinggi. Konversi tersebut berpotensi menyebabkan degradasi ekosistem gambut serta meningkatkan risiko kebakaran hutan dan lahan. Namun, keterbatasan data spasial jangka panjang mengenai dinamika perubahan tutupan dan penggunaan lahan di KHG Kabupaten Rokan Hilir masih menjadi hambatan dalam mendukung pengelolaan gambut yang berkelanjutan. Penelitian ini bertujuan untuk menganalisis kelas tutupan dan penggunaan lahan yang paling banyak mengalami perubahan serta mengestimasi luas perubahannya pada periode 2005-2023. Klasifikasi dilakukan menggunakan algoritma *Random Forest* dengan 12 indeks sebagai variabel *input*. Tutupan dan penggunaan lahan diklasifikasikan menjadi enam kelas, yaitu badan air, lahan terbangun, lahan terbuka, perkebunan sawit, hutan alam, dan hutan tanaman. Hasil penelitian menunjukkan bahwa selama periode 2005-2023, kelas yang mengalami penurunan luas terbesar adalah hutan alam sebesar 119.186,3 ha dan hutan tanaman sebesar 72.135,6 ha. Sementara itu, peningkatan luas terbesar terjadi pada perkebunan sawit sebesar 146.384,7 ha dan lahan terbangun sebesar 22.101,2 ha.

Kata kunci: Degradasi, gambut, *random forest*, tutupan dan penggunaan lahan

1. Introduction

Indonesia is among the countries with the largest proportion of tropical peatlands, accounting for approximately 36% of the world's tropical peatland area (Warren et al., 2017). The total peatland area in Indonesia covers 14,905,600 ha, concentrated on three major islands: Kalimantan (28-32% of Indonesia's total peatland area), Sumatra (34-43%), and Papua (25-38%) (Harrison et al., 2020). Riau Province has a tropical peatland area of 6.5 million ha, distributed across several districts in the form of Peat Hydrological Units (PHU) (Khaira et al., 2020). According to Turmudi et al. (2021), the Government of Indonesia has designated peatland areas within the framework of PHU.

A PHU is a peatland area that is hydrologically interconnected and serves as an instrument to ensure the sustainability of peatlands. Its boundaries are typically defined by natural features such as rivers, coastlines, or mineral topographic divides, where surface and groundwater within the peat are interconnected in a single system. Peatlands remain sustainable when they are permanently or seasonally water-saturated (Harun et al., 2020). Conversely, they are prone to degradation if disruptions occur in their hydrological cycle, as this cycle plays a vital role in peatland persistence.

Rokan Hilir is one of the regencies in Riau Province, covering a total area of 888.159 ha, including both peatland and non-peatland areas. The peatlands in this regency form the Rokan Hilir KHG, covering approximately 592,730.2 ha of its total area (Mubekti, 2011). However, a significant proportion of these peatlands has undergone land-use conversion. Large-scale peatland expansion has been driven primarily by the plantation sector, along with industrial and residential development (Awal et al., 2023). According to Masganti et al. (2014), peatland degradation in Riau Province currently covers around 2,313,561 ha or 59.54% of its total peatland area. Of this 1,037,020 ha are utilized by local communities for oil palm cultivation, food crops, and horticulture (Wahyunto et al., 2013). Land-cover and land-use change has significantly contributed to peatland fires in Rokan Hilir Regency. In 2015, approximately 189,491 ha of peatland in the regency were burned (Harnanda, 2021). Activities that increase peat fire vulnerability include canal construction, the use of fire for land clearing in plantation areas, and forest encroachment (Fesyuk et al., 2020).

Sustainable peatland ecosystem protection is crucial, given its vital role for human well-being. Monitoring land use land cover change is necessary to serve as a basis for evaluating land use and formulating policies to protect peatlands vulnerable to degradation. Initially, land cover monitoring was conducted through field surveys and manual visual interpretation. However, these methods are inefficient as they require substantial time and resources (Feng et al., 2022). Currently, land cover monitoring can be carried out indirectly through remote sensing techniques. Google Earth Engine (GEE) is one such platform capable of performing land cover classification. According to Feng et al. (2022), GEE is a cloud-based geospatial processing platform used for preprocessing and acquiring multitemporal imagery that has been filtered. This monitoring process utilizes multispectral sensors from satellite imagery, along with various band algorithms and the processing of vegetation, water, and built-up indices (Firmansyah et al., 2022).

This study aims to analyze the land cover and land use types that have undergone the most significant changes and to estimate the area of land cover and land use with the greatest changes in the Rokan Hilir Peat Hydrological Unit (PHU) from 2005 to 2023.

2. Methodology

2.1. Research Location

This study was conducted from September 2024 to January 2025, utilizing secondary data obtained through remote sensing in the Rokan Hilir Peatland Hydrological Unit (PHU), Riau Province. Data processing and interpretation were carried out at the Department of Silviculture, Faculty of Forestry and Environment, IPB University. The study area focused on the Rokan Hilir PHU, which has been identified as an area frequently experiencing land-cover and land-use changes in Riau Province (Figure 1). Geographically, the regency is located between 1°14′-2°45′ N and 100°17′-101°21′ E.

The tools used in this study included stationery, GEE, Google Drive, Microsoft Excel 2021, Microsoft Word 2021, ArcGIS 10.8, Google Earth Pro, and RStudio software for data visualization. The materials used comprised shapefiles of the Rokan Hilir PHU, district boundaries, regency boundaries, and provincial boundaries, as well as Landsat Landsat imagery.

2.2. Methods

2.2.1. Data Acquisition and Sample Collection

This study used secondary data consisting of Landsat satellite imagery and administrative boundary data. Landsat imagery was obtained from the GEE platform, including Landsat 5 Thematic Mapper (TM), Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS), and Landsat 9 Operational Land Imager-2/Thermal Infrared Sensor-2 (OLI-2/TIRS-2). The imagery used in this study was Landsat Collection 2 Level-2 Surface Reflectance. The data were selected to represent three observation periods, namely 2005, 2015, and 2023, within the boundary of the Rokan Hilir Peat Hydrological Unit (PHU). Sample collection was conducted through visual interpretation and digitization of points/polygons to generate training and validation datasets. The samples were categorized into six land.

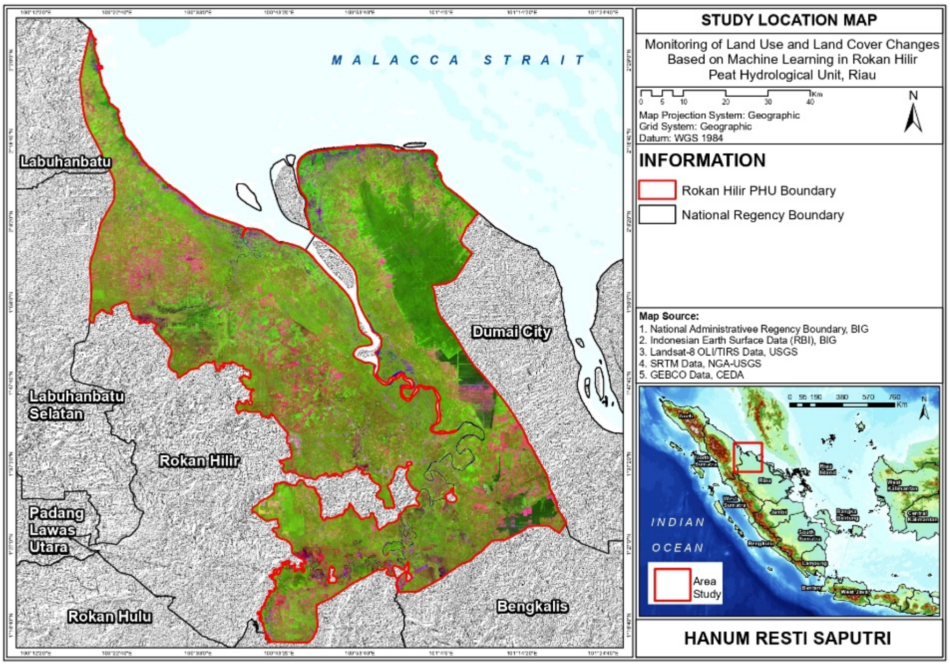

Figure (*Gambar*) 1. Research location (*Lokasi penelitian)*

Use/land cover (LULC) classes water body, built-up, bare land, oil palm plantation, natural forest, and plantation forest (Table 1). Sampling was performed in areas considered stable during the 2005–2023 period to ensure consistency of reference data across all observation years. The samples were subsequently verified using high-resolution imagery from Google Earth Pro to confirm the accuracy of class interpretation. The sample dataset was then divided into 70% training data and 30% validation data, where the training data were used for model development and the validation data were used for accuracy assessment.

2.2.2. Research Procedures

The study was conducted through several stages, including data inventory, sampling, image preprocessing, land use/land cover (LULC) classification using the Random Forest (RF) machine learning algorithm, and accuracy assessment. The overall research workflow is presented in Figure 2. Image preprocessing was performed to improve data quality prior to the classification process. This stage included image clipping based on the area of interest (AOI), cloud and cloud-shadow masking, and the generation of annual composite images to obtain cleaner and more stable representations for each observation year. Subsequently, spectral band calculations and derived spectral indices were generated to enhance class separability among land cover and land use types. A total of 12 spectral indices were used as input variables for classification, including vegetation indices, water indices, and built-up indices. The list of indices is presented in Table 2.

LULC classification was conducted using the RF algorithm. RF is an ensemble-based machine learning method that constructs multiple decision trees to improve prediction accuracy and model stability. This algorithm is considered effective for remote sensing classification due to its ability to handle high-dimensional data and reduce bias in classification results (Breiman, 2001). The classification outputs produced LULC maps for 2005, 2015, and 2023, which were subsequently used to analyze changes in the area of each class within the study region.

Table (*Tabel)* 1. Land use land cover classification system (*Sistem klasifikasi tutupan dan penggunaan lahan*)

Class (*Kelas*)	Description (*Deskripsi*)
Water Body	All types of water body, dominated by natural and artificial waters such as rivers, lakes, ponds, and seas. Includes canals or artificially constructed channels with a linear water width > 30 m (Feng et al., 2022).
Built-up	Includes urban areas, rural settlements, and industrial lands that are strongly influenced by human activities (Saijow et al., 2016).
Bare Land	Areas without vegetation cover, including plantations and industrial timber estates (ITE) in post-harvest conditions (Iskandar et al., 2023).
Oil Palm Plantation	Areas with non-woody vegetation cover, specifically planted with oil palm trees (Permen 2021)
Natural Forest	Areas with natural vegetation cover dominated by broadleaf trees with a canopy cover greater than 60% (Feng et al., 2022)
Plantation Forest	Areas with monoculture vegetation cover cultivated for industrial purposes, such as Industrial Timber Estates (ITE) (Permen, 2021)

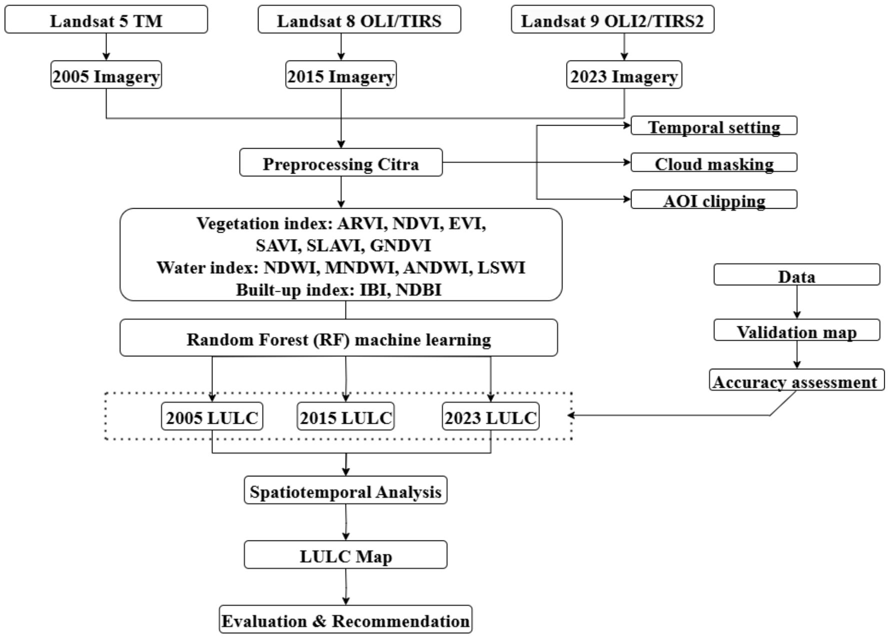

Figure (*Gambar*) 2. Diagram flow chart (*Diagram alir penelitian*)

Table (*Tabel*) 2. List of indices used (*Daftar indeks yang digunakan*)

No	Method (*Metode*)	Formula (*Rumus*)	Reference (*Pustaka*)
1.	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR - (Red - (Blue - Red))) / NIR + (Red - (Blue - Red)))	Kaufman & Tenre (1992)
2.	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Rouse jr et al., (1974)
3.	Enhanced Vegetation Index (EVI)	EVI = G ((NIR - Red) / (NIR + C1 x Red - C2 x Blue + L))	Huete et al., (2002)
4.	Soil Adjusted Vegetation Index (SAVI)	SAVI = 1.5 (NIR - Red)/ (NIR + Red + 0.5)	Huete (1988)
5.	Specific Leaf Area Vegetation Index (SLAVI)	SLAVI = NIR / (Red + SWIR)	Lymburner et al., (2000)
6.	Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = (NIR - Green) / (NIR + Green)	Gitelson et al., (1996)
7	Normalized Difference Water Index (NDWI)	NDWI = (Green - NIR) / (Green + NIR)	McFeeters (1996)
8	Modified Normalized Difference Water Index (MNDWI)	MNDWI = (Green - SWIR1) / (Green + SWIR1)	Xu (2006)
9	Normalized Difference Water Index (ANDWI)	ANDWI = (Blue + Green + Red - NIR - SWIR1 - SWIR2) / (Blue + Green + Red + NIR + SWIR1 + SWIR2	Rad et al., (2021)
10	Land Surface Water Index (LSWI)	LSWI = (NIR - SWIR) / (NIR + SWIR)	Xiao et al., (2002)
11	Index- Based Built- up Index (IBI)	IBI = ((NIR)/NIR + Red)) + ((Green)/Green + SWIR1))	Xu (2008)
12	Normalized Difference Built-up Index (NDBI)	NDBI = (SWIR - NIR) / (SWIR + NIR)	Zha et al., (2003)

2.2.3. Accuracy Assessment

Accuracy assessment was conducted to evaluate the reliability of the land use/land cover (LULC) classification results. The validation dataset was used as reference data and compared with the classified LULC maps for each observation year. Classification accuracy was evaluated using a confusion matrix, which represents the agreement between the reference classes and the predicted classes produced by the model. Based on the confusion matrix, several accuracy metrics were calculated, including overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and the kappa statistic (KS). Overall accuracy represents the proportion of correctly classified samples relative to the total validation samples. Producer accuracy indicates the probability that a reference sample is correctly classified, while user accuracy reflects the probability that a sample classified into a given category truly represents that category on the ground. The kappa statistic was used to measure the level of agreement between the classification results and reference data beyond chance agreement (Novianti, 2021; Muhammad et al., 2016). The equations for OA, PA, UA, and KS are presented in the following formulas.

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

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

$$UA = \frac{X_{ii}}{X_{+i}} \times 100\%$$

$$PA = \frac{X_{ii}}{X_{i}} \times 100\%$$

Notes:
OA : *Overall Accuracy*
KS : *Kappa Statistic*
UA : *User Accuracy*
PA : *Producer Accuracy*
r : Number of rows and columns in the confusion matrix
N : Total number of observations (pixels)
Xii : Observations in the corresponding row and column
X + 1 : Total column margin
Xi : Total row margin

3. Results and Discussion

3.1. Results

RF classification is used to observe the pattern of land cover and use changes in the Rokan Hilir KHG, Riau Province. Land cover and use classification is carried out in 6 different classes from 2005 to 2023. Changes in land cover and use of an area over time are seen in Figures 3, 4, and 5.

The water body, built-up, bare land, oil palm plantation, natural forest, and plantation forest in the Rokan Hilir PHU experienced significant increases and decreases in area. The conversion area and direction of LULC change from 2005 to 2023 are shown in Table 3. Changes in LULC at this location are also depicted in the form of a percentage area graph (Figure 6).

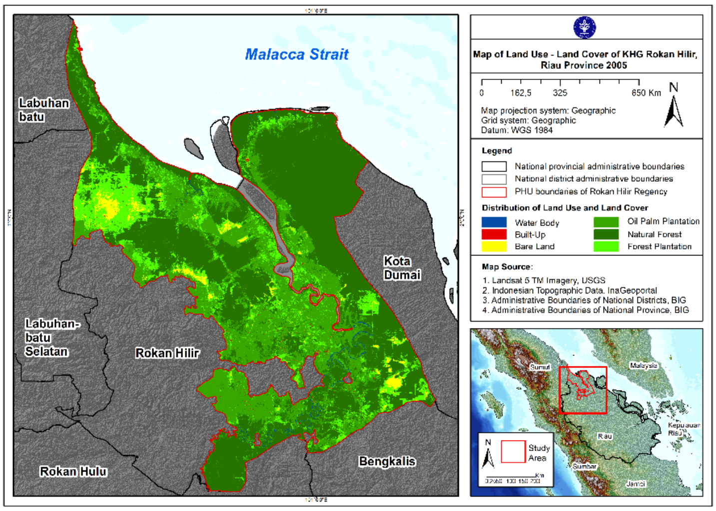

Figure (*Gambar*) 3. LULC of PHU Rokan Hilir on 2005 (Tutupan dan penggunaan lahan KHG Rokan Hilir tahun 2005)

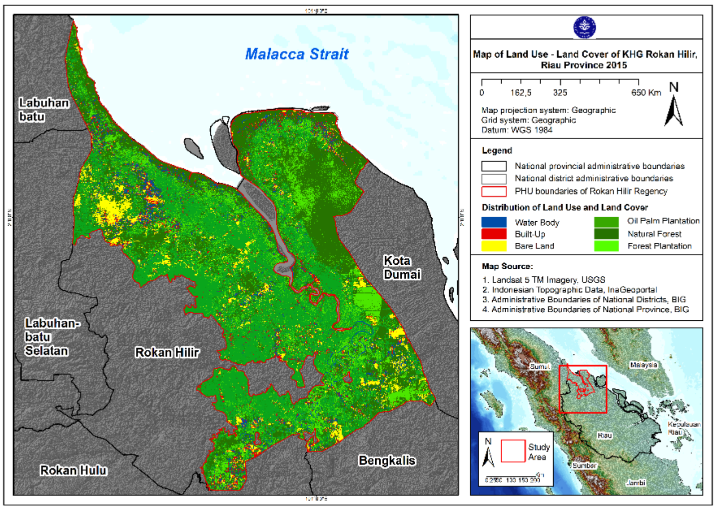

Figure (*Gambar*) 4. LULC of PHU Rokan Hilir on 2015 (Tutupan dan penggunaan lahan KHG Rokan Hilir tahun 2015)

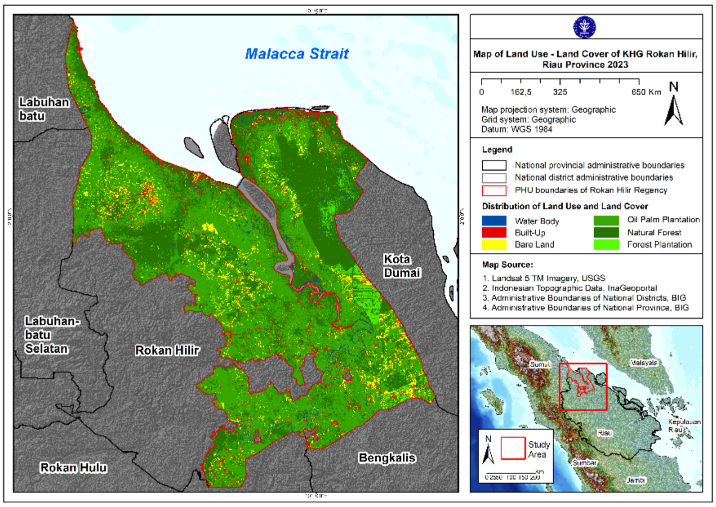

Figure (*Gambar*) 5. LULC of PHU Rokan Hilir on 2023 (Tutupan dan penggunaan lahan KHG Rokan Hilir tahun 2023)

Table (*Tabel*) 3. Extent and direction of LULC change from 2005-2023 (Luas dan arah perubahan LULC tahun 2005-2023)

Year (*Tahun*)	Water body/Badan air (ha)	Built-up/Lahan terbangun (ha)	Bare land/Lahan terbuka (ha)	Oil palm plantation/ Perkebunan sawit (ha)	Natural forest/ Hutan alam (ha)	Plantation forest/ Hutan tanaman (ha)
2005	3,520.0	1,038.8	13,469.8	194,331.4	341,770.1	85,573.6
2015	29,354.3	18,826.6	37,552.1	256,566.6	211,393.0	85,996.1
2023	6,367.0	23,140.0	33,438.2	340,716.1	222,583.8	13,438.0
Difference between 2005 to 2023	+2.847,0	+22.101,2	+19.968,4	+146.384,7	-119.186,3	-72.135,6

(+) increases, (-) decreases

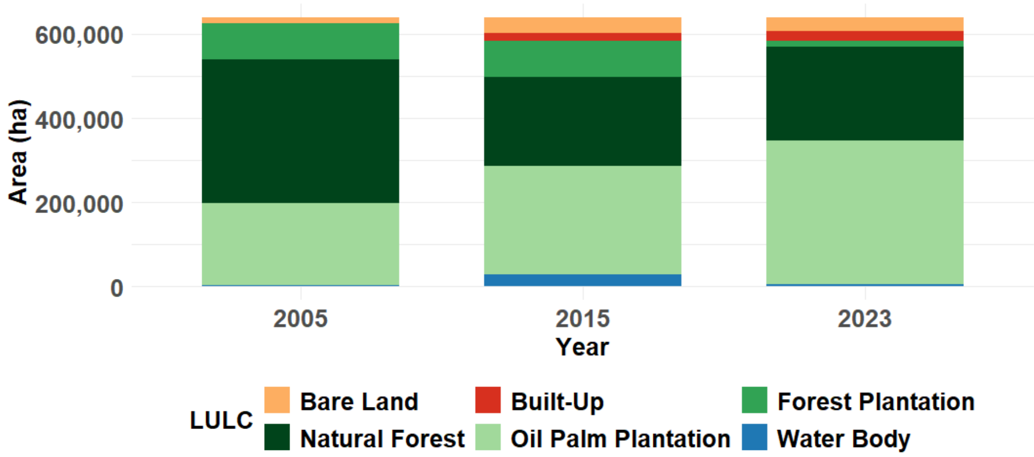

Figure (*Gambar*) 6. Classification area in KHG Rokan Hilir 2005-2023 (Luas klasifikasi di KHG Rokan Hilir tahun 2005-2023)

Land use land cover class that experienced the greatest expansion was oil palm plantation. The largest decrease in area occurred in natural forest and plantation forest, which were converted into other land-use classes. The extent LULC change matrix during 2005-2015 and 2015-2023 are presented in Tables 4 and 5.

The classification process in GEE has limited performance if it is not supported by the use of spectral indices. These indices are applied to assist decision-making within the RF classification algorithm. The contribution of each index is evaluated using the Variable Importance (VI) method. Madinu et al., (2024) reported that, in satellite image classification using the GEE platform, the VI feature represents a major advantage, as it identifies the most influential input variables. Spectral indices ranked by VI serve as critical inputs for the RF machine learning algorithm during the classification process. Classification accuracy strongly depends on the algorithm's ability to discriminate reflectance values among different land use land cover types. Therefore, the selection of spectral index algorithms that are sensitive to a wide range of land-cover types is crucial. The use of less sensitive indices has a high potential to introduce errors in the final classification results. A total of 12 spectral indices were used to classify six highly heterogeneous LULC classes (Figure 7).

Table (*Tabel)* 4. LULC change matrix for 2005-2015 (Matriks perubahan LULC tahun 2005-2015)

	Water body/ Badan air (ha)	Natural forest/ Hutan alam (ha)	Forest plantation /Hutan tanaman (ha)	Built-up/ Lahan terbangun (ha)	Bare land/ Lahan terbuka (ha)	Oil palm plantation/ Perkebunan sawit (ha)	Changes in area/ Luas perubahan (ha)
Water body (ha)	2,740	577	71	16	29	56	3,488
Natural forest (ha)	15,704	160,155	53,381	10,298	19,219	82,932	341,689
Forest plantation (ha)	5,860	23,100	9,521	4,452	10,389	32,230	85,553
Built-up (ha)	72	114	35	415	281	121	1,038
Bare land (ha)	411	3,098	754	267	3,704	5,236	13,469
Oil palm plantation (ha)	4,521	24,296	22,221	3,373	3,924	135,936	194,272
Change in area 2015 (ha)	29,307	211,340	85,984	18,820	37,546	256,511	639,509

Table (*Tabel)* 5. LULC change matrix for 2015-2023(Matriks perubahan LULC tahun 2015-2023)

	Water body/ *Badan air* (ha)	Natural forest/ *Hutan alam* (ha)	Forest plantation/ *Hutan tanaman* (ha)	Built-up/ *Lahan terbangun* (ha)	Bare land/ *Lahan terbuka* (ha)	Oil palm plantation/ *Perkebunan sawit* (ha)	Changes in area/*Luas perubahan* (ha)
Water body (ha)	3,228	6,593	109	2,381	2,073	14,931	29,316
Natural forest (ha)	1,708	115,915	5,245	8,520	11,692	68,261	211,340
Forest plantation (ha)	387	28,248	6,446	2,637	4,325	43,941	85,983
Built-up (ha)	217	4,446	177	3,581	1,266	9,134	18,821
Bare land (ha)	203	9,721	929	2,256	3,595	20,842	37,545
Oil palm plantation (ha)	589	57,603	530	3,759	10,483	183,530	256,495
Changes in Area 2023 (ha)	6,333	222,525	13,435	23,134	33,433	340,640	639,500

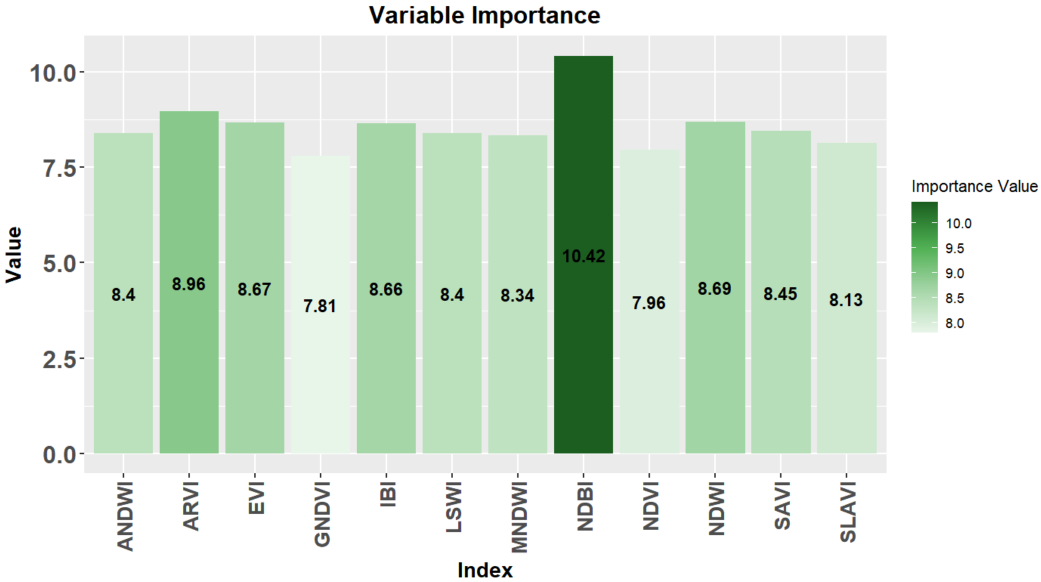

Figure (*Gambar*) 7. Important variables index (Indeks variabel penting)

After the land cover and land use change analysis was completed, the data were organized into confusion matrices presented in Tables 6, 7, and 8. These matrices provide information on the number of correctly and incorrectly classified training samples, the allocation of classification errors, and the evaluation of classification accuracy for the years 2005–2023. From these matrices, user accuracy, overall accuracy, producer accuracy, and the kappa statistic can be calculated. Overall accuracy represents the proportion of pixels correctly classified according to their true class, producer accuracy assesses how well pixels are classified into the designated categories, and user accuracy indicates the potential classification error (Duan et al., 2019). Furthermore, the results of the user accuracy (UA), producer accuracy (PA), kappa statistic (KS), and overall accuracy (OA) calculations are presented in graphical form in Figures 8 and 9.

Table (*Tabel)* 6. Matrix confusion 2005 (Konfusi matriks tahun 2005)

2005		Actual (*Aktual*)					
		Water body/Badan air	Built-up/Lahan terbangun	Bare land/Lahan terbuka	Oil palm plantation/Perkebunan sawit	Natural forest/Hutan alam	Plantation forest/Hutan tanaman
Predictions	Water body	**479**	0	0	0	0	0
	Built-up	0	**26**	0	0	0	0
	Bare land	0	0	**564**	0	0	34
	Oil palm plantation	0	0	0	**522**	0	5
	Natural forest	3	0	0	6	**218**	532
	Plantation forest	7	2	5	0	1	**1942**

Table (*Tabel)* 7. Matrix confusion 2015 (Konfusi matriks tahun 2015)

2015		Actual (*Aktual*)					
		Water body/Badan air	Built-up/Lahan terbangun	Bare land/Lahan terbuka	Oil palm plantation/Perkebunan sawit	Natural forest/Hutan alam	Plantation forest/Hutan tanaman
Predictions	Water Body	**47**	4	0	0	0	0
	Built-Up	0	**20**	0	0	0	0
	Bare Land	0	0	**805**	0	0	0
	Oil Palm Plantation	0	0	0	**353**	71	2
	Natural Forest	1	3	0	25	**306**	524
	Plantation Forest	0	0	0	138	19	**1575**

Table (*Tabel)* 8. Matrix confusion 2023 (Konfusi matriks tahun 2023)

2023		Actual (*Aktual*)					
		Water body/Badan air	Built-up/Lahan terbangun	Bare land/Lahan terbuka	Oil palm plantation/Perkebunan sawit	Natural forest/Hutan alam	Plantation forest/Hutan tanaman
Predictions	Water Body	**174**	0	0	0	1	0
	Built-up	0	**105**	8	4	6	3
	Bare Land	0	44	**367**	0	0	32
	Oil Palm Plantation	0	0	0	**331**	64	3
	Natural Forest	0	0	0	19	**371**	0
	Plantation forest	0	3	3	15	78	**265**

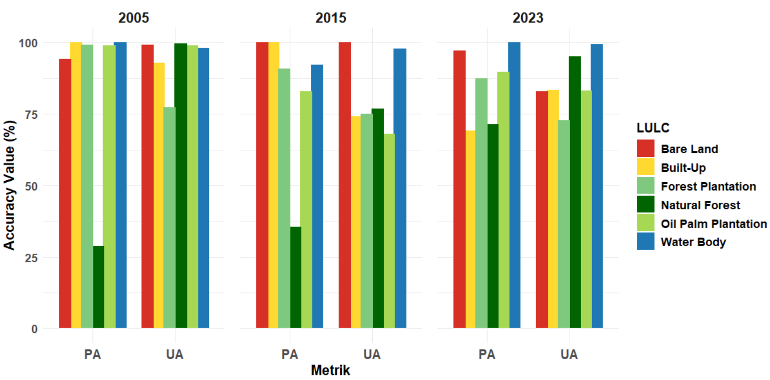

Figure (*Gambar*) 8. Comparison of UA and PA values of RF (Perbandingan nilai UA dan PA dari RF)

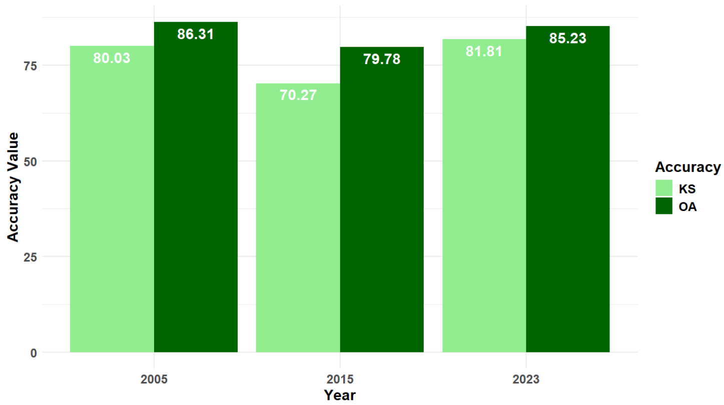

Figure (*Gambar*) 9. Comparison of Overall Accuracy (OA) and Kappa Statistic (KS) values of RF (*Perbandingan nilai Overall Accuracy (OA) dan Kappa Statistic (KS) dari RF*)

Table (*Tabel)* 9. OA and KS values from the classification results (*Nilai OA dan KS dari hasil klasifikasi*)

Observation year/*Tahun pengamatan*	Kappa statistic/*Statistik Kappa* (KS) (%)	Overall accuracy/*Akurasi keseluruhan* (OA) (%)
2005	80.03	86.31
2015	70.27	79.78
2023	81.81	85.23

Based on Figure 9 and Table 9, the RF machine learning algorithm demonstrated varying classification accuracy performance across the observation years. In 2005, the classification achieved its highest accuracy level, with an OA value of 86.31% and a kappa reaching 80.03%. However, a decline in accuracy performance occurred in 2015, where the OA dropped to 79.78% and the KS decreased to 70.27%. This decline represents the lowest accuracy point among the three analyzed observation periods, resulting from high spectral overlapping among several land cover classes during that year. The classification accuracy then recovered in 2023, recording an OA value of 85.23% and a KS of 81.81%. This resurgence in accuracy during the final observation year indicates that the utilization of a 12-spectral-index combination within the GEE platform successfully optimized the separation of land cover object characteristics.

3.2. Discussion

3.2.1. Land Use Land Cover Change

Land use and land cover concepts that are often used interchangeably, but they have fundamental differences. Cihlar & Jansen (2001) briefly define land cover as the natural state of the land, while land use is human activity that alters or utilizes that natural state. Furthermore, Montalván-Burbano et al., (2021) define land use as related to land management, and refers to humans utilizing land, water, and plants for their own benefit. Land cover describes the characteristics of the Earth's surface landscape. Land use relates to how humans utilize the land, such as for agriculture, settlements, or industry. On the other hand, land cover refers to everything that covers the land surface, be it vegetation, buildings, water, or other types of land cover.

The changes observed in the study area during the 2005-2023 period reflect the dynamics and trends of physical regional development. Land cover and land use changes in the Rokan Hilir Peat Hydrological Unit (KHG) were identified by comparing the area of each land use type between 2005 and 2023, providing an overview of spatial distribution patterns, including both increases and decreases in each land cover and land use category. The monitoring results indicate a decrease in the extent of natural forest and plantation forest, amounting to 119,186.3 ha and 72,135.6 ha, respectively. In contrast, there were increases in water body (2,847.0 ha), built-up (22,101.2 ha), bare land (19,968.4 ha), and oil palm plantation (146,384.7 ha) (Table 3). The magnitude of these changes indicates a clear trend, where the decline in natural and plantation forest alongside the expansion of oil palm plantation and built-up land suggests that landscape transformation did not occur sporadically, but rather consistently over time. This pattern demonstrates that the dominant direction of change in the peatland landscape within the study area tends toward forest conversion into cultivated land and built-up.

This condition is consistent with findings that Riau Province, particularly Rokan Hilir Regency, experienced forest loss and plantation expansion between 1999 and 2020, much of which occurred on peatlands (Numata et al., 2022). The most rapidly developed plantation type was oil palm. Forest reduction due to the expansion of oil palm plantation, especially on peatlands, is associated with the limited availability of suitable land on mineral soils (Numata et al., 2022). Increasing demand for plantation land has placed significant pressure on natural forest cover types (Obeidat et al., 2019). Plantation activities also require good accessibility for transportation and mobility, thereby driving the expansion of built-up such as roads, often at the expense of vegetation. According to Syahza (2019), the development of oil palm plantation in Riau has been very rapid, which aligns with the results of this study. The rapid growth of oil palm plantation in Riau is driven by several key factors, including favorable physical and environmental conditions for cultivation, a strategic geographical location that facilitates access to international markets, and Riau’s involvement in regional economic growth zones that provide broader and more profitable market opportunities. In addition, income from oil palm has been proven to be higher than that from other plantation commodities, attracting farmers to expand oil palm cultivation (Purba & Sipayung, 2017).

The expansion of built-up land has occurred alongside the growth of oil palm plantation and has shown a consistent increase over the years. This rise in built-up is closely related to population growth in Rokan Hilir Regency, Riau. According to the Regional Regulation (Perda, 2017), the population of Rokan Hilir reached 644,680 in 2015, with an average annual growth rate of 4.58% during the 2000–2010 period. This high growth rate is influenced by demographic dynamics such as birth rates, mortality rates, and migration patterns (Sakti & Ikhwan, 2019). Population growth increases land demand for residential areas, commercial activities, and industrial development (Manakane et al., 2023). The expansion of built-up land is also closely linked to the rapid development of oil palm plantation, as the dominance of oil palm reflects the growth of palm oil industries in the study area. Population growth and intensified plantation-related activities have driven the need for additional space to support settlements and related infrastructure. Therefore, the spatiotemporal dynamics of land use and land cover (LULC) patterns must be interpreted carefully, as they are influenced by both natural factors and human activities that drive changes in land use and land cover (Tesfaye et al., 2024). Fluctuations in land cover area during the 2005–2023 period indicate significant changes in land use and land cover within the Rokan Hilir Peat Hydrological Unit.

Based on the intersection analysis of LULC classification results for the 2005–2015 period, natural forest experienced the largest conversion into oil palm plantation, covering an area of 82,932 ha, while the conversion from oil palm plantation back to natural forest amounted to only 24,296 ha. The greatest decrease in classification occurred in plantation forest, which were converted into oil palm plantation over an area of 32,230 ha, whereas the reverse conversion from oil palm plantation into plantation forest covered only 22,221 ha. In addition, natural forest were also substantially converted into built-up land, with an affected area of 10,298 ha. During the subsequent period (2015–2023), a similar conversion pattern persisted. Natural forest were again converted into oil palm plantation over an area of 68,261 ha, while conversion from oil palm plantation into natural forest reached 57,603 ha. The largest classification decrease also occurred in plantation forest, which were converted into oil palm plantation across 43,941 ha, whereas the reverse conversion from oil palm plantation into plantation forest was extremely limited, amounting to only 530 ha. These findings confirm that forest conversion into oil palm plantation has been the dominant driver of land cover change in the study area and further indicate that development pressure and cultivation activities have continued intensively within the Rokan Hilir peatland ecosystem.

3.2.2. Land Use Land Cover Change

The variable importance (VI) values of the spectral indices contributing to the classification of land use and land cover (LULC) classes in the Rokan Hilir Peat Hydrological Unit (PHU) are presented in Figure 7. The Normalized Difference Built-up Index (NDBI) showed the highest VI contribution (10.42%), whereas the Green Normalized Difference Vegetation Index (GNDVI) exhibited the lowest contribution (7.81%). This pattern is noteworthy, as NDBI ranked as the most influential index despite the study area being located within a peat hydrological unit, which is typically characterized by waterlogged soils and is generally dominated by vegetation and surface water. The high contribution of NDBI can be explained by its strong sensitivity to dense built-up surfaces and exposed soil, suggesting that substantial portions of the Rokan Hilir PHU have been converted into built-up areas and bare land.

Nevertheless, several indices exhibited relatively similar spectral responses across multiple LULC classes, particularly between plantation forest and natural forest, as well as between bare land and built-up areas, which contributed to classification errors. Asy'Ari et al. (2023) reported that land cover classification performance may be affected by inappropriate index selection and limitations in the quantity and quality of training data. Furthermore, classification of heterogeneous land cover classes remains challenging, as emphasized by Ghemire et al. (2010), due to high intra-class variability and complex landscape artifacts. Therefore, careful consideration of index sensitivity and discriminative capability based on pixel-level values is essential to improve class separability prior to conducting LULC classification.

The classification results indicate that the highest error rates occurred in the oil palm plantation, plantation forest, and natural forest classes. Misclassification frequently occurred among these three land cover types, where pixels classified as natural forest were often incorrectly identified as oil palm plantation or plantation forest, and vice versa. This reflects substantial spectral overlap among vegetated classes, causing the classification model to struggle in distinguishing land cover types with similar canopy structure and vegetation density. In contrast, classes such as water bodies, built-up areas, and bare land exhibited relatively fewer classification errors due to their more distinct spectral characteristics compared to vegetated land cover types. The difficulty in differentiating vegetated classes such as forests and oil palm plantations is primarily attributed to the similarity and overlap of spectral index values across these land cover types (Rivai, 2023).

Based on the user accuracy (UA) and producer accuracy (PA) results (Figure 8), the highest classification accuracy was achieved for the water body class, with UA and PA values ranging from 95% to 100%. This indicates that water bodies exhibit clear and consistent spectral characteristics, allowing them to be reliably identified by the classification model. Conversely, the natural forest class showed the lowest accuracy, with UA and PA values displaying a wide range from 25% to 99%. This substantial variation suggests that classification performance for natural forest was strongly influenced by the limitations of the algorithm in discriminating reflectance among vegetated classes, as well as by landscape complexity that increases variability in spectral index values within the same class. In addition, lower UA and PA values may also be influenced by the quality of reference data used for training and accuracy assessment. Errors or inconsistencies in reference data may propagate through the classification process and contribute to reduced classification accuracy.

Overall classification performance was further evaluated using Overall Accuracy (OA) and the Kappa Statistic (KS) (Figure 9). The results indicate that spatial information on annual LULC patterns was obtained with relatively high accuracy. The highest KS value was recorded in 2023, while the highest OA value was achieved in 2005, with values of 81.81% and 86.31%, respectively. The resulting Kappa values fall within the almost perfect agreement category, indicating a strong level of agreement between classification results and reference data, and confirming that the classification outputs are reliable for spatiotemporal land cover change analysis. The application of geospatial technology using the Random Forest (RF) algorithm produced satisfactory classification performance, although some misclassification remained, particularly among vegetated land cover classes. The integration of spectral index algorithms and RF-based machine learning within the Google Earth Engine (GEE) platform plays an important role in filtering pixels from multi-temporal image collections within each year, thereby improving the consistency and reliability of classification results (Wandani et al., 2022).

Classification uncertainty may propagate into LULC change estimation, particularly for transitions among spectrally similar vegetated classes. Consequently, some detected changes may reflect classification noise rather than actual land cover conversion. This indicates that change detection accuracy is strongly dependent on the classification accuracy of each year. However, the consistently high OA and KS values across the study period suggest that the main spatiotemporal change trends remain reliable for landscape-scale interpretation. Overall, the accuracy assessment confirms that LULC mapping in the Rokan Hilir PHU achieved good reliability at the landscape scale and can be used to analyze spatiotemporal land cover change dynamics. However, interpretation of changes among vegetated classes such as natural forest, plantation forest, and oil palm plantations should be conducted cautiously due to the potential for misclassification arising from spectral similarity and vegetation heterogeneity.

4. Conclusion and Recommendations

4.1. Conclusion

The greatest area declines in the Rokan Hilir Peat Hydrological Unit (PHU) during the 2005–2023 period occurred in natural forest and plantation forest, which were primarily converted into oil palm plantation and built-up. Natural forest and plantation forest cover in the Rokan Hilir PHU decreased by 119,186.3 ha and 72,135.6 ha, respectively, between 2005 and 2023. In contrast, land-use classes represented by oil palm plantation and built-up increased by 146,384.7 ha and 22,101.2 ha, respectively, over the same period.

4.2. Recommendations

Studies on land-use and land-cover change using remote sensing technology remain essential, as they facilitate and accelerate data acquisition over large spatial extents in a time-efficient manner. Nevertheless, field-based ground checks are strongly recommended as a validation step to ensure data accuracy and to capture on-site conditions that may not be fully detected by satellite imagery. The interpretation results derived from remote sensing can then be compared with field observations to assess their consistency and to enhance the reliability of the analysis outcomes.

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