Research Article

Monitoring Land Use and Land Cover Using Remote Sensing Technology in Kubu Raya Regency, West Kalimantan Province

Monitoring Tutupan dan Penggunaan Lahan Menggunakan Teknologi Remote Sensing di Kabupaten Kubu Raya, Provinsi Kalimantan Barat

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Abstract: *Kubu Raya Regency is one of the areas that has a peat ecosystem in it. The peat ecosystem has a role and function in mitigating climate change because it has the ability to store quite high carbon reserves. However, peat ecosystems often experience degradation and changes in land cover which can contribute carbon emissions to the atmosphere. Remote sensing is a technology that can be used to detect changes in land cover and use in Kubu Raya Regency. Therefore, this research aims to detect changes in land cover and using remote sensing technology and assess the level of accuracy of the detection results. Analysis of changes in land cover and use from 2000 - 2023 was obtained by guided classification using the Random Forest (RF) algorithm which involves various vegetation, water and built-up land indices. The research results show that there is a decrease in forest land area from 2000 to 2023 amounting to 106,542 ha. The forest area in 2000 was 524,359 ha, while in 2023 it will be 417,817 ha. The results of accuracy measurements show an overall accuracy (OA) value of 98.84% with a kappa statistic of 0.98. It is hoped that the results of these findings will provide an initial picture of the condition of the ecosystem in Kubu Raya Regency, most of which is a peat ecosystem, as a consideration in formulating peat ecosystem conservation policies.*

Keywords: LULC, Peatland, Random Forest, Remote Sensing

Abstrak: Kabupaten Kubu Raya merupakan salah satu daerah yang memiliki ekosistem gambut di dalamnya. Ekosistem gambut memiliki peran dan fungsi dalam mitigasi perubahan iklim karena memiliki kemampuan menyimpan cadangan karbon yang cukup tinggi. Akan tetapi, ekosistem gambut sering kali mengalami degradasi dan perubahan tutupan lahan yang dapat menyumbang emisi CO2 ke atmosfer. *Remote sensing* merupakan salah satu teknologi yang dapat digunakan dalam mendeteksi perubahan tutupan dan penggunaan lahan di Kabupaten Kubu Raya. Oleh karena itu, penelitian ini bertujuan mendeteksi perubahan tutupan dan penggunaan lahan menggunakan teknologi *remote sensing* dan menilai tingkat akurasi hasil deteksi. Analisis perubahan tutupan dan penggunaan lahan dari tahun 2000 - 2023 diperoleh dengan cara klasifikasi terbimbing menggunakan algoritma *Random Forest* (RF) yang melibatkan berbagai indeks vegetasi, air, dan lahan terbangun. Hasil penelitian menunjukkan bahwa terdapat penurunan luas lahan hutan dari tahun 2000 sampai 2023 sebesar 106.542 ha. Luas hutan tahun 2000 sebesar 524.359 ha, sedangkan pada tahun 2023 sebesar 417.817 ha. Hasil penilaian akurasi menunjukkan nilai *overall accuracy* (OA) sebesar 98,84% dengan *kappa statistik* 0,98. Hasil deteksi ini diharapkan dapat menjadi gambaran awal kondisi ekosistem di Kabupaten Kubu Raya yang sebagian besar merupakan ekosistem gambut sebagai pertimbangan dalam penyusunan kebijakan pengelolaan ekosistem gambut.

Kata kunci: LULC, Gambut, *Random Forest*, *Remote Sensing*

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INTRODUCTION

Peat ecosystems have a crucial role in wetland landscape area. Peat ecosystem in their natural state make an important contribution to regional and global biodiversity and provide a vital but undervalued habitat, for rare and threatened species (Wösten et al. 2008). Peatlands are formed from organic material that accumulates on the earth's surface over a long period (Saputri et al. 2024). Peat and biodiversity is a negative and or low population in peatland area because soil acid level, unsuitable of fauna habitat. Sudrajat (2019) explains that peatlands play an important role in mitigating global climate change, and this role makes peat ecosystems essential to protect. Peat ecosystems also function as carbon reservoirs and water storage for surrounding areas (Ratmini 2012). Indonesia has extensive peatlands spread across its islands, one of which is located in Kubu Raya Regency, West Kalimantan Province. Kubu Raya Regency, with its rich and vital peatlands, often experiences degradation. Peatland degradation occurs due to several factors, such as fires and mining activities. Masganti et al. (2014) also explain that peatland degradation is largely caused by destructive human activities. Degraded peatlands experience a decline in their functions and productivity, which in turn impacts the surrounding ecosystem.

As the population increases, the demand for land also rises, whether for housing or plantations. This has become one of the causes of changes in Land Use and Land Cover (LULCC) in Kubu Raya Regency, particularly in peat ecosystems. Land-use change is essentially a trade-off between modifying terrestrial ecosystems for the positive benefit of providing food and fiber for human consumption and possible negative repercussions on other ecosystem services (Mustard et al. 2012). LULCC can affect the biophysical and socio-economic conditions of the community, thus impacting land sensitivity and accelerating the land degradation process (Bajocco et al. 2012). The acceleration of the degradation process can be a serious threat to biodiversity if not handled seriously. In this advanced era, these changes can be monitored through remote sensing technology, where spatial planning and decision-making related to land use policies can be facilitated by analyzing data obtained from this technology (Nurda & Habibie 2023).

Google Earth Engine (GEE) is one of the geospatial technology widely used by researchers for monitoring land cover and change dynamic. Its use requires specific computer script codes to obtain the desired data. Kumar & Mutanga (2018) state that addressing environmental issues using big data processing can be achieved through GEE, which is specifically designed to manage large volumes of data that often pose challenges for researchers utilizing satellite imagery. GEE also offers numerous advantages, such as an abundance of data layers available on the platform, and users can easily share computer codes, enabling even those less skilled in coding to conduct earth observation studies. Research on monitoring LULCC using machine learning technology is very limited in Kubu Raya peatland landscape. Therefore, this research aims to detect changes in LULC using remote sensing technology and assess the accuracy of the detection results.

MATERIALS AND METHODS

Research Location

This research was conducted in November 2024, using secondary data obtained through remote sensing in Kubu Raya Regency, West Kalimantan Province. Data processing and interpretation were carried out at IPB University. Geographically, Kubu Raya Regency Figure 1 is located between 108°35′ BT – 109°58′ BT and 0°44′ LU – 1°01′ LS. Kubu Raya Regency is located at the forefront of West Kalimantan Province, which is directly adjacent to Mempawah Regency, Pontianak City and Landak Regency to the north, Sanggau Regency and Ketapang Regency to the East, Kayong Utara Regency to the South and Karimata Strait to the West.

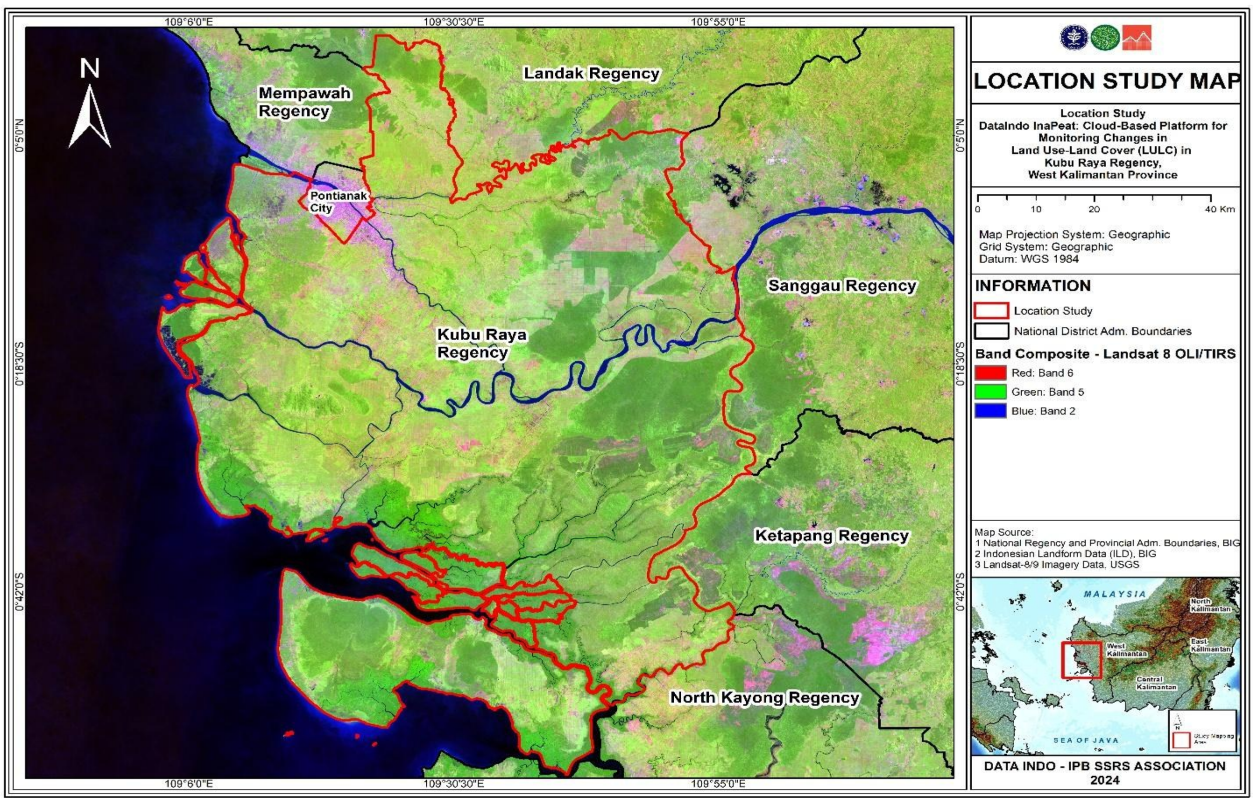

Figure 1. Research location

Data Source and Research Workflow

The tools used in this research include Google Earth Engine, R-Studio, Microsoft Excel 2021, Microsoft Word 2021, and ArcGIS 10.8. The materials used are Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) image data, and Indonesian Topographic Maps. Monitoring LULC change in this study involves satellite imagery obtained through Google Earth Engine (GEE). Two types of satellite imagery were used: Landsat 5 TM for data from 2000-2010 and Landsat 8 OLI/TIRS for data from 2015-2023. Data processing in this study was carried out by land cover mapping to see areas with different covers such as water, plantations, built-up land, open land, and forest. The research flow diagram is presented in Figure 2.

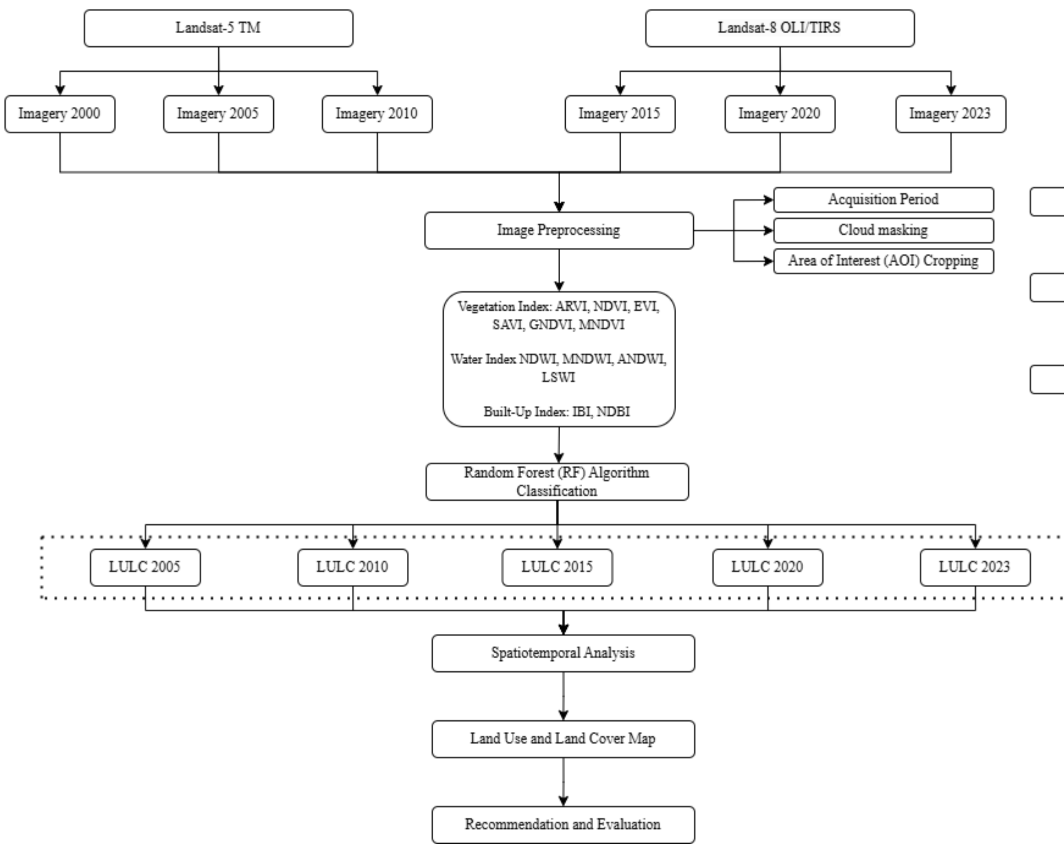

Figure 2. Research flow diagram

Data Processing and Analysis

LULC Classification

The analysis used in this study involved a machine learning classification algorithm, namely Random Forest (RF), which took place on the Google Earth Engine (GEE) platform and continued on the ArcMap platform for the data visualization stage. Random Forest is based on the classification of trees. The RF method includes classification and clustering methods based on an ensemble of decision trees or decision trees (Ali et al. 2023). This study also used three types of indices, namely vegetation, water, and built-up (Table 1).

Table 1. List of involved indexes

No	Index	Formula	Reference
1.	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR - (Red - (Blue - Red))) / NIR + (Red - (Blue -Red)))	Kauffman & Tanre (1992)
2.	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	
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)	Rouse et al (1974)
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.	Modified Normalized Difference Vegetation Index (MNDVI)	MNDVI = (Red Edge 2 - Red Edge 1) / (Red Edge 2 + Red Edge 1)	Xu (2006)
8.	Normalized Difference Water Index (NDWI)	NDWI = (Green - NIR) / (Green + NIR)	
9.	Modified Normalized Difference Water Index (MNDWI)	MNDWI = (Green - SWIR1) / (Green + SWIR1)	Xu (2006)
10.	Normalized Difference Water Index (ANDWI)	ANDWI = (Blue + Green + Red - NIR - SWIR1 - SWIR2) / (Blue + Green + Red + NIR + SWIR1 + SWIR2	Rad et al (2021)
11.	Land Surface Water Index (LSWI)	LSWI = (NIR - SWIR) / (NIR + SWIR)	Xiao et al (2002)
12.	Index- Based Built- up Index (IBI)	IBI = ((NIR)/NIR + Red)) + ((Green)/Green + SWIR1))	Xu (2008)
13.	Normalized Difference Builtup Index (NDBI)	NDBI = (SWIR - NIR) / (SWIR + NIR)	Zha et al (2003)

Google Earth Engine Platform: Classification and Training Data

Google Earth Engine (GEE) is a cloud computing-based mapping platform that has the ability to process large amounts of data and process it in a short time. GEE is included in the platform that exists because of the development of remote sensing technology. According to Rahmawati & Asy'Ari (2021), data processing within this platform follows a script that has been created. The built script is connected to resources in the form of satellite imagery that will be used either Landsat or Sentinel as needed. Data processing is done by classifying the types of LULC in Kubu Raya Regency, West Kalimantan Province. To distinguish areas based on different classes, training is taken that is considered to represent the type of LULC. In this study, 137 trainings were offered in total, with the amount of training in each class corresponding to the area's size. The GEE platform used for classification and training areas can be seen in Figure 3.

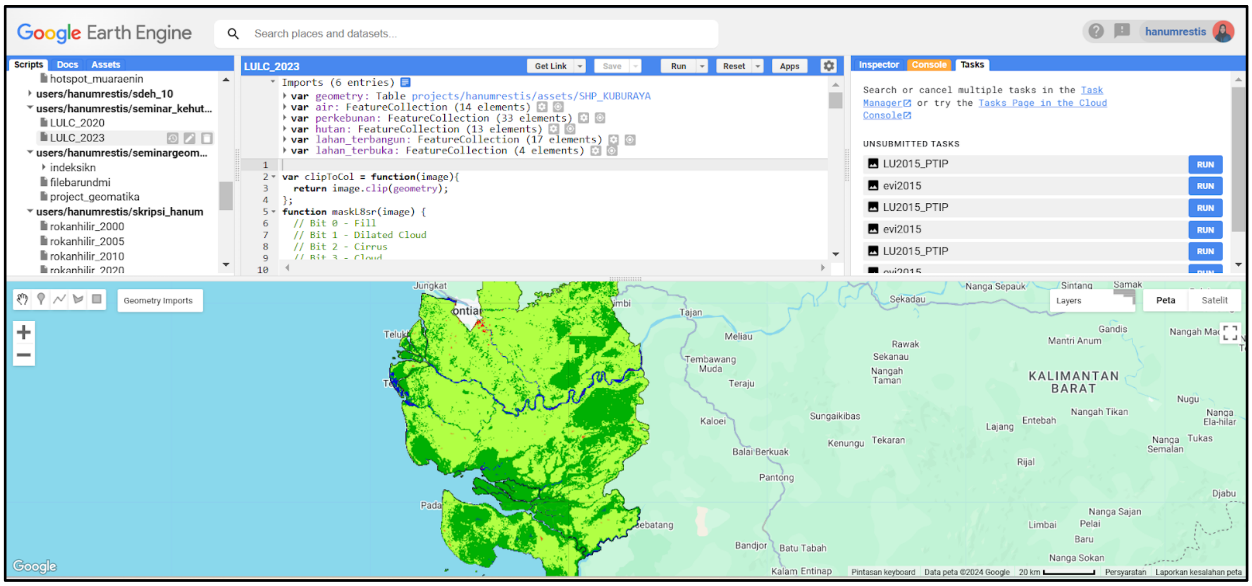

Figure 3. Google Earth Engine platform

Accuracy Assessment

Remote sensing approaches often produce spatial information that doesn't fully reflect actual field conditions. Therefore, systematic testing is needed to evaluate the accuracy of the detection results through accuracy assessment methods (Diesing et al. 2014). This step is also crucial before the spatial information from this research is shared with users (Congalton & Green 2019). This research includes an accuracy level analysis, which includes Overall Accuracy (OA) and Kappa Statistics (KS). Accuracy testing is performed using 5782 validation data obtained through image processing on the Google Earth Engine platform. This analysis is carried out by testing all the results of monitoring LULC based on the indices used to achieve optimal accuracy levels. The test results using the Kappa Statistics formula refer to the classification of value interpretation as shown in Table 2, which has been previously designed and is a commonly applied approach in data quality testing.

$$Kappa\ Statistic = \frac{N\ \sum_{i=1}^{\gamma}\ X_{ii} - \sum_{i=1}^{\gamma}\ X_{i+}X_{+1}}{N\sum_{i=1}^{\gamma}\ X_{i+}X_{+1}}$$

$$User's\ Accuracy = \frac{X_{ii}}{X_{+i}} \times\ 100\%$$

$$Producer's\ Accuracy = \frac{X_{ii}}{X_i} \times 100\%$$

$$Overall\ Accuracy = \frac{\sum_{i=1}^{Y} X_{ii}}{N}$$

The validation data used in this study were generated and selected through the Google Earth Engine (GEE) platform by considering the characteristics of the satellite imagery in the classification period. The process of observing image characteristics was carried out by forming an image composite through the RGB feature in GEE, using various bands available on the Landsat satellite. The location of the validation data distribution was determined based on the type of land cover and its use from year to year. The distribution of validation points designed for accuracy testing is shown in Figure 3.

Table 2. Interpretation of kappa values

Kappa Values	Description
<0.00	*Poor*
0.00-0.20	*Slight*
0.21-0.40	*Fair*
0.41-0.60	*Moderate*
0.61-0.80	*Substantial*
0.81-1.00	*Almost perfect*

Source: Madinu et al. (2024)

RESULTS AND DISCUSSION

Spatial of Land Use Land Cover Change

Based on Figure 4, it can be seen that the classification of land cover classes in Kubu Raya Regency consists of water bodies, plantations, open land, built-up land, and forests. The results of the LULC classification analysis obtained from 2 types of satellite imagery, namely Landsat 5 TM and Landsat 8 OLI/TIRS, show that the largest land cover area in 2000 was wetland forest in the form of swamp forest and mangrove forest, with an area of 524,359 ha Figure 4. Meanwhile, the second largest land cover classification is plantations with an area of 308,225 ha. The third largest land cover classification is water bodies with an area of 18,310 ha consisting of seas, lakes, rivers, and ponds. The fourth largest is open land with an area of 2,753 ha. Open land in the field can be in the form of open fields, newly harvested plantation land, and mining land. Built-up land is the smallest land cover classification with an area of 49 ha which can be in the form of settlements, factories, warehouses, offices and buildings.

Based on the classification results in Figure 4, land cover in Kubu Raya Regency in 2023 is still dominated by the forest land cover class, which has decreased in area to 417,817 ha. Meanwhile, built-up land is one of the land cover classes that has experienced the largest increase in area in 2023 with an increase in area reaching 1,820 ha. The land cover classification that experienced the second largest increase in area was plantations with an area of 411,632 ha.

Changes in LULC that occur from one LULC to another with the aim of meeting increasing human needs over time are a manifestation of LULC change (Nath et al. 2021). LULC change can also be defined as the change of one LULC to another and is directly or indirectly related to human goals to meet their needs (Darvishi et al. 2020). Changes in LULC in Kubu Raya Regency from 2000-2023 showed an increase in the types of LULC for plantations, barren land and built up, while the types of forest and water body land cover experienced a decrease in area. Forest is the LULC that has the highest decrease in area from 2000-2023, while water bodies experienced the second highest decrease in area.

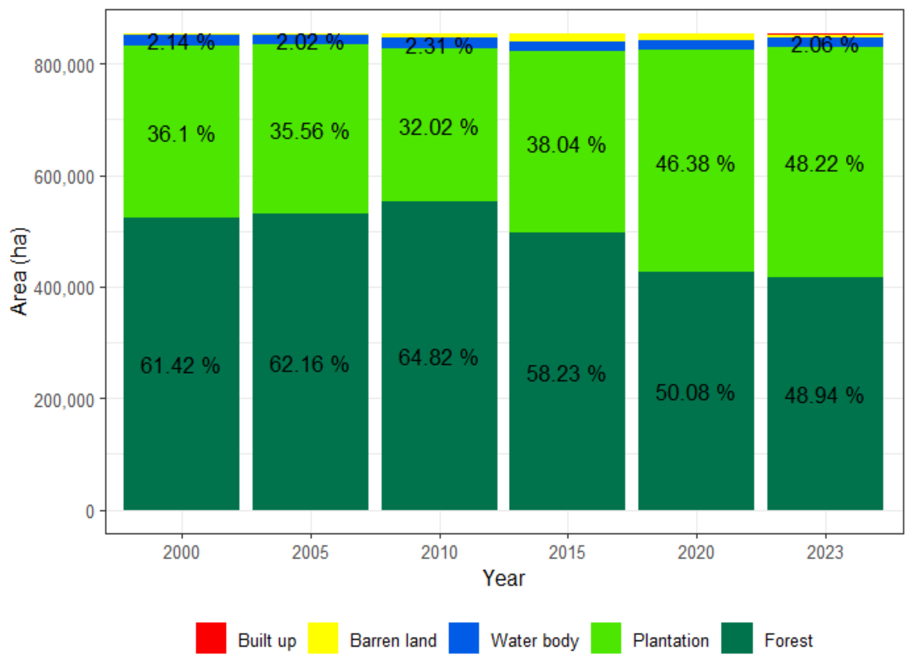

Figure 4. Area of LULC classification

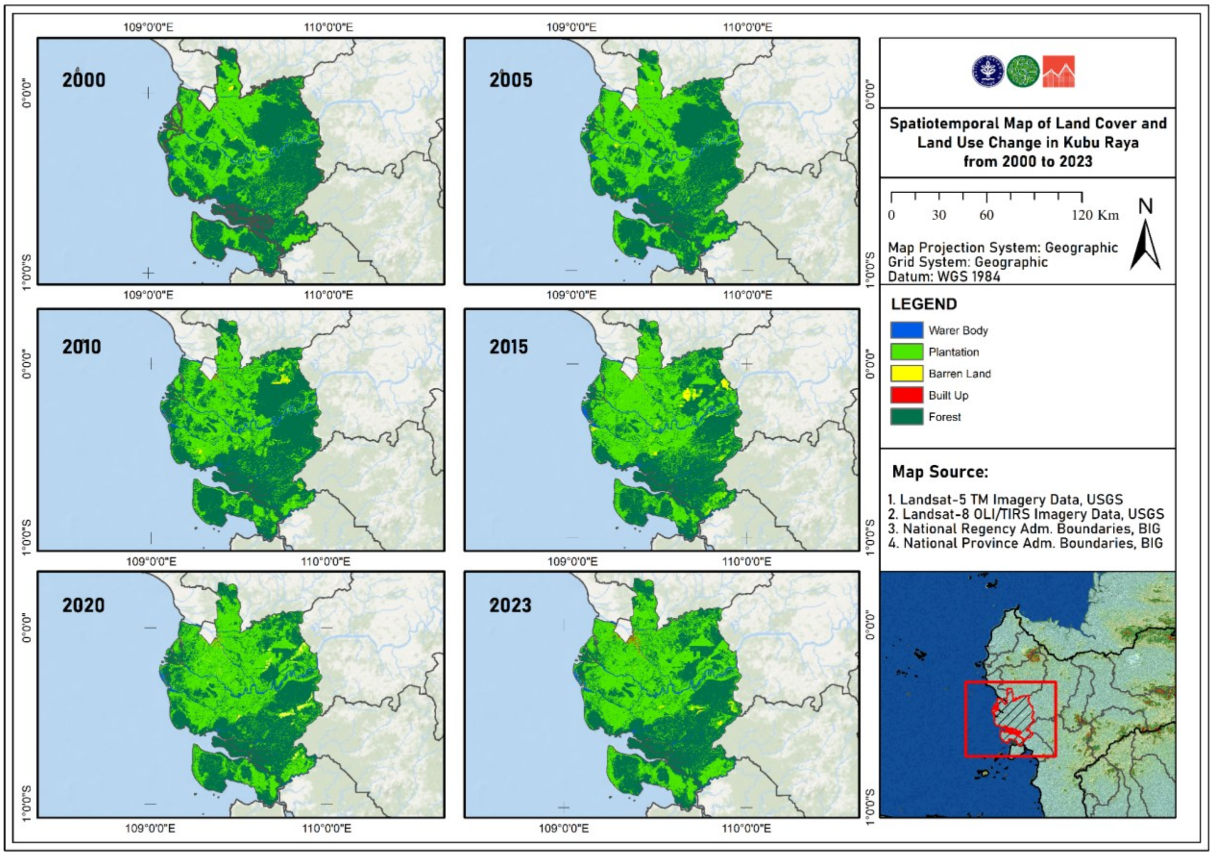

Figure 5. Spatiotemporal LULC classification map

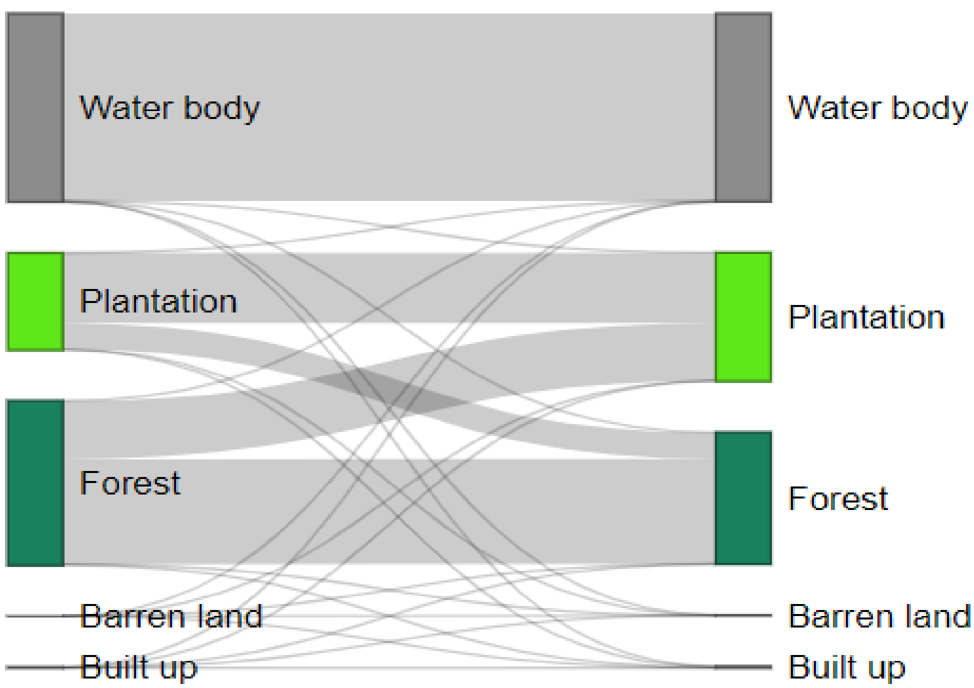

Figure 6. Direction of change in LULC

Figure 5 shows that land cover is still dominated by forests and plantations. The largest land cover change occurred in the forest land cover classification with an area of 524,359 ha in 2000 and decreased to 417,817 ha in 2023. Figure 6 shows that most of the forest land cover classification has been converted to plantation land cover. This can also be seen through the area of plantation land which continues to expand from 308,225 ha to 411,632 ha. Forest land cover appears to have changed to open land in 2010 and 2015 as preparation for additional plantation area. This can occur due to uncontrolled deforestation to meet the needs of company-scale plantation land use, which can increase the rate of forest cover change (Graeub et al. 2016) and (Austin et al. 2017). The most extensive plantation in Kubu Raya Regency, West Kalimantan is an oil palm plantation owned by the company (Triyono et al. 2015). The use of plantation land that can grow rapidly in Kubu Raya Regency is caused by the ease of granting and extending permits by the government and has a large contribution to increasing regional income or Regional Original Income (ROI) (Zulkarnain 2014).

Classification Accuracy

The accuracy assessment results show Overall Accuracy (OA) and Kappa Statistic (KS) values of 98.84% and 0.98, respectively (Table 3). he OA and KS values are classified as nearly perfect (Table 2). Analysis of land cover and land use classification requires an accuracy test or assessment. This is necessary to assess the accuracy of the classification so that the classification results can provide classification information properly. A total of 5782 data were used for accuracy assessment. The accuracy assessment was carried out using a confusion matrix in Table 3. The level of accuracy is strongly influenced by the training data and the indices used Rahmawati et al. (2022) and Rivai et al. (2023). Forests and plantations are land cover classifications with the lowest accuracy. Forests and oil palm plantations have similar spectral characteristic values, making it possible for misclassification to occur.

Table 3. Results of the assessment of the accuracy of LULC classification

	Validation Data						User's Accuracy (%)
Type of Land Use	Water Body	Plantation	Forest	Built Up	Barren Land	Total	
Water Body	589	0	0	0	0	589	100
Plantation	0	1820	29	0	0	1849	98,43
Forest	0	19	2683	0	0	2702	99,30
Built Up	0	12	0	135	6	153	88,24
Barren Land	0	1	0	0	488	489	99,80
Total	589	1852	2712	135	494	5782	
Producer's Accuracy (PA)	100	98,27	98,93	100,00	98,79		

Overall Accuracy (OA)	98,84%
Kappa Statistic (KS)	0,98

CONCLUSIONS

The research results indicate that there have been changes in land cover and land use detected through remote sensing technology. The area of forest land in Kubu Raya Regency from 2000 to 2023 has decreased by 106,542 ha, while the plantation area has increased from year to year. The supervised classification model using the random forest algorithm shows good results in detecting and analyzing land classification data because it can eliminate overfitting from decision trees by producing an Overall Accuracy (OA) value of 98.84% and a Kappa Statistic (KA) of 0.98. Therefore, the classification of land cover and land use change using RF on the GEE platform is expected to provide an initial overview of the ecosystem conditions in Kubu Raya Regency, which is mostly a peat ecosystem, as a consideration in the preparation of peat management policies, not only in Kubu Raya but also in other regions.

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