

LAND USE CHANGE PATHWAYS IN THE BARUMUN WATERSHED: ASSESSING THE ROLE OF OIL PALM EXPANSION

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ABSTRACT

Indonesia is among the world's major palm oil producers, and oil palm expansion is often associated with deforestation. This study examines gradual land use and land cover (LULC) changes from 2000 to 2023 in the Barumun watershed, North Sumatra, using Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) imagery processed through Google Earth Engine. A Random Forest (RF) machine learning algorithm was applied for supervised classification. The results indicate that forest cover decreased by 5.12% over 23 years. The primary conversion pathway was forest to other land with tree cover (accounting for up to 54.60% of initial forest loss), which was later converted to oil palm plantations. Oil palm area increased by 13.91%, but direct forest-to-oil palm conversion was limited. These findings suggest that oil palm was not the primary cause of initial deforestation in this watershed. The results provide evidence for policymakers to distinguish between direct and indirect land use change pathways when designing sustainable land management strategies.

Keywords: Land use land cover change, oil palm plantation, random forest, remote sensing, sustainability.

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INTRODUCTION

Oil palm, which originated in Africa, is now cultivated extensively in tropical regions of Africa, Asia and Latin America. Compared with other vegetable oil crops, oil palm uses land relatively efficiently. According to Oil World data by ISTA Mielke GmbH (2021), in 2020, oil palm accounted for 36.5% of global vegetable oil production while using less than 9% of the available cropland. This indicates that oil palm is a highly efficient crop in terms of productivity. This condition has driven the rapid expansion of oil palm in Indonesia, Malaysia, and other tropical countries to meet increasing demand for vegetable oil. In Indonesia, the palm oil industry contributes positively to foreign exchange earnings and society more broadly (Sunarminto et al., 2019). In Malaysia, palm oil production generates economic benefits through exports of

26.66 million tonnes of palm oil and palm-based products, reflecting its importance in global supply chains, while contributing 2.5%–3.6% of gross domestic product (GDP) and earning RM108–RM138 billion in strong price years (Mat Enh et al., 2025; Parveez et al., 2026).

Oil palm cultivation is a major economic activity for farmers in Labuhan Batu Regency, North Sumatra, Indonesia. This reliance on oil palm has significant implications for the long-term sustainability of agribusiness in the region (Suardi et al., 2022). The Barumun watershed was selected because it represents a major watershed in North Sumatra, covering 13,482 km² and considered one of the largest in the region. It encompasses 89.7% of the total watershed area and serves as a primary source of oil palm plantations (Munthe et al., 2025). Although the watershed is not among the largest oil palm production areas nationally, it is highly representative of the indirect and gradual land-use transitions that characterise many oil palm landscapes in Sumatra. This context allows the study to capture incremental transformation pathways that are often overlooked in analyses focused on major deforestation hotspots.

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The rapid expansion of oil palm plantations in Indonesia has intensified ongoing concerns about land-use change. Globally, land-use change is a major concern from environmental, social and economic perspectives. Rapid population growth in many countries has substantially influenced land-use change and conservation at both regional and global scales (Li et al., 2017). Land use and land cover (LULC) products are essential for studying land dynamics, particularly those related to environmental and socioeconomic concerns (Wang et al., 2023). Previous studies have shown that 98.56% of prospective oil palm plantation areas are not forests but are instead designated as other land use areas (54.93%) and plantations or agriculture (42.19%), based on the origin of oil palm plantation status reported by Santosa et al. (2020). According to Gatto et al. (2015), although oil palm has expanded significantly, rubber remains the dominant crop because it is cultivated on previously used land, whereas oil palm plantations are often established on newly converted land. Oil palm plantations are not always the primary direct cause of deforestation (Austin et al., 2017; Gaveau et al., 2022). In addition, land-use change often occurs gradually, as logging companies and illegal logging activities convert forests into scrub and bushes before these areas are repurposed for cropland, bare land, or plantations (Dharmawan et al., 2020). For example, rubber plantations cover 52.00% of the land in Southern Sumatra, Indonesia (Pratiwi et al., 2021). Rubber expansion has also contributed to forest landscape alteration in Malaysia (Abdullah & Nakagoshi, 2007) and forest displacement in Thailand (Saswattecha et al., 2016).

LULC change is driven by both natural and human factors. Understanding these changes provides government agencies and other institutions with a basis for prioritising land and environmental management (Gidado et al., 2018). Remote sensing (RS) has been widely applied in LULC studies. RS and Geographic Information Systems (GIS) use high-resolution satellite imagery to observe and generate land-use and land-cover patterns (Rawat & Kumar, 2015). Random Forest (RF) was selected for LULC classification because it is effective in handling the nonlinear and high-dimensional spectral data commonly found in vegetation-dominated landscapes. RF has been widely used in RS-based LULC mapping and demonstrates stable performance with limited sensitivity to parameter tuning (Avci et al., 2023; Sheykhmousa et al., 2020). Although other classifiers, such as Support Vector Machines (SVM), are also well established and often yield comparable results, this study prioritised methodological consistency across multi-temporal analyses rather than inter-algorithm comparison. Accurate LULC classification is crucial for obtaining reliable LULC

data (Atef et al., 2023). RS supports the production of accurate LULC maps by using high-quality Landsat images, suitable classification techniques, and expert interpretation (Rwanga & Ndambuki, 2017). Google Earth Engine (GEE) was used to acquire Landsat data and improve processing efficiency. GEE provides cloud computing services that enable analysis of more than 40 years of Landsat data (Patel et al., 2015) and supports large-scale applications with high accuracy and precision (Nasiri et al., 2022). Basheer et al. (2022) compared land-change analysis using GEE and ArcGIS Pro and found that ArcGIS Pro achieved higher accuracy, although the difference was not statistically significant.

Numerous recent studies have used these tools for data visualisation and advanced geospatial analysis. Various methods have been developed to improve the accuracy and precision of LULC mapping, including unsupervised and supervised image classification, non-parametric machine learning, and deep-learning-based classification approaches (Talukdar et al., 2021). According to the literature, SVM and RF are among the most widely used algorithms in this context (Avci et al., 2023). RF can achieve higher accuracy when trained with larger datasets. The core of this method is the construction of decision trees, each of which evaluates the classification of each pixel (Svoboda et al., 2022).

The RF analysis is commonly used in land-cover studies, as demonstrated by Kulkarni et al. (2016). The RF model can be used to extract primary LULC categories at the river-basin scale and can serve as an operational monitoring technique that provides near-real-time results (Pareeth et al., 2019). RF is widely applied in multi-temporal LULC classification because it is a non-parametric supervised classification technique that efficiently handles large databases, analyses numerous input variables, and achieves a high level of accuracy (Rodriguez-Galiano et al., 2012; Svoboda et al., 2022). Method evaluation typically considers factors such as training sample size, sensitivity to noise and changes in classifier parameters that influence RF performance (Belgiu & Dragu, 2016).

Despite ongoing debate, a critical research problem remains: High-resolution temporal evidence is still limited regarding the specific land-conversion pathways that lead to oil palm expansion. Most studies and prevailing narratives often imply a direct, one-step conversion from forest to oil palm plantation. However, land change is frequently a complex, multi-stage process involving intermediate land uses. This gap leads to a second applied problem: Without accurately diagnosing the sequence of land-use change, policies aimed at curbing deforestation and promoting sustainable commodities risk being ineffective or unfair. For

instance, if forests are first cleared for other annual crops or timber plantations before later conversion to oil palm, policies that focus solely on oil palm may address a symptom rather than the root cause of initial forest loss.

To address these problems, this study investigates three questions in the Barumun watershed: (1) What are the dominant long-term LULC change trends from 2000 to 2023? (2) what is the primary sequence or pathway of forest conversion? and (3) to what extent can oil palm expansion be directly attributed to initial deforestation in this region?

MATERIALS AND METHODS

Study Area

The study is located in the Barumun watershed, North Sumatra Province, Indonesia, between

$0^{\circ} 50' 00''$ N, $98^{\circ} 40' 00''$ E and $2^{\circ} 40' 00''$ N, $100^{\circ} 50' 00''$ E. The total study area is 1,321,454.61 ha (Figure 1). The watershed encompasses seven administrative regions and is traversed by two main rivers, the Barumun and Bilah, which discharge into the Strait of Malacca.

Data Acquisition

The preprocessing steps comprised the selection of Landsat surface reflectance imagery, cloud and cloud-shadow masking, image compositing for each analysis period, spatial subsetting to the Barumun watershed boundary, band selection and harmonisation between Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) sensors, and preparation of training and validation samples before RF classification.

The Landsat images were divided into five periods between 2000 and 2023 and acquired from GEE (Table 1). This platform provides access

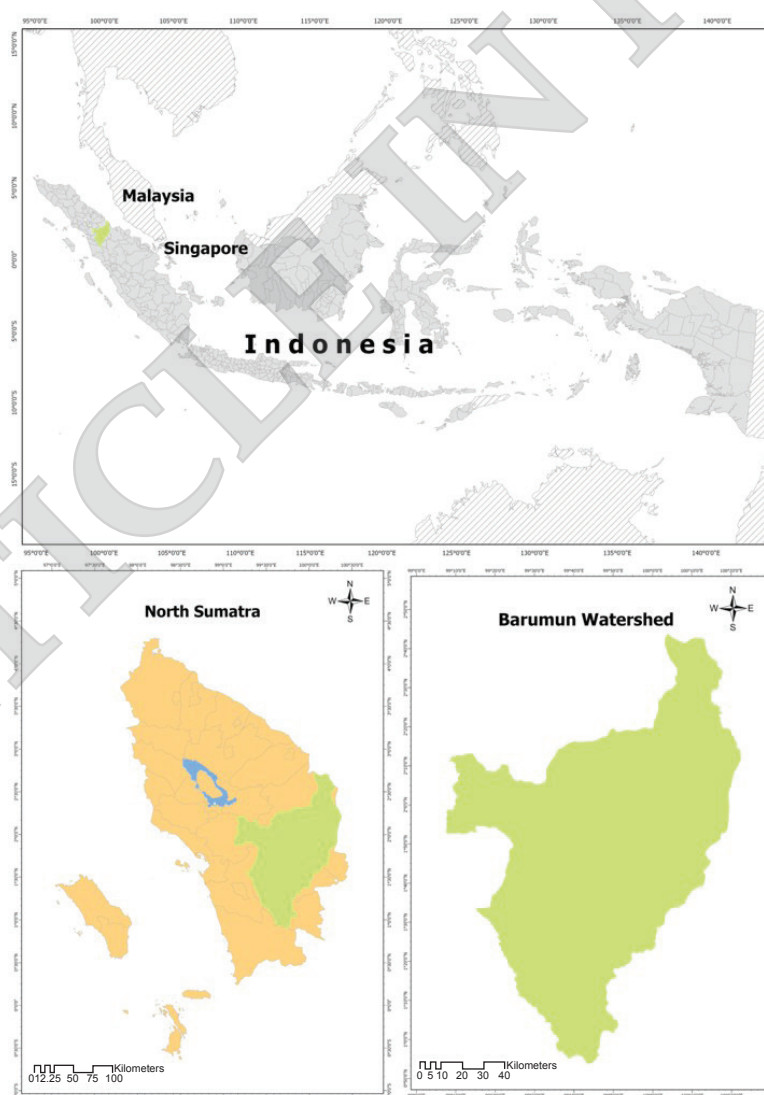


Figure 1. Area of study.

TABLE 1. DATA TABLE

No.	Data type	Satellite/Sensor	Spatial resolution	Temporal resolution	Analysis period	Acquisition years
1	Multispectral satellite imagery	Landsat 5 TM	30 m	16 days (revisit cycle)	Period 1	2000–2005
2	Multispectral satellite imagery	Landsat 5 TM	30 m	16 days (revisit cycle)	Period 2	2006–2010
3	Multispectral satellite imagery	Landsat 8 OLI/TIRS	30 m (multispectral)	16 days (revisit cycle)	Period 3	2011–2015
4	Multispectral satellite imagery	Landsat 8 OLI/TIRS	30 m (multispectral)	16 days (revisit cycle)	Period 4	2016–2020
5	Multispectral satellite imagery	Landsat 8 OLI/TIRS	30 m (multispectral)	16 days (revisit cycle)	Period 5	2021–2023

Note: TM - Thematic Mapper; OLI - Operational Land Imager; TIRS - Thermal Infrared Sensor.

to extensive datasets and supports large-scale geospatial processing. LULC classification used Landsat 5 TM images with a 30 m resolution from 2000 to 2010 and Landsat 8 OLI images from 2011 to 2023.

Research Flowchart

Satellite images are crucial for understanding land-use change. This study used supervised classification to categorise land use based on Landsat imagery, as shown in Figure 2. This technique requires image analysts to apply algorithms that analyse pixels using the numerical descriptions of LULC contained within the images. Training samples were selected to represent the defined LULC types. To analyse data using RF, a commonly used algorithm for classifying RS data (Millard & Richardson, 2015), independent error evaluation and iterative classification were conducted to assess the reliability of the predicted classes.

Image preparation. Landsat thematic maps were obtained from GEE for 2000–2023 at a pixel resolution of 30 m. Cloud-free composite images were produced by combining multiple images taken at different times. The GEE platform was selected to address challenges related to optimal image coverage, cloud minimisation (Liu et al., 2018), and processing power limitations (Adepoju & Adelabu, 2020). Xie et al. (2019) stated that GEE is advantageous for land classification because it provides abundant satellite data from multiple sources and high-performance computing resources. The GEE preprocessing script used in this study is available at: <https://code.earthengine.google.com/ed9001c7a838c7e7db98564e0b734595>. GEE was used for data access and cloud screening because it provides efficient access to multi-temporal Landsat archives and enables rapid identification of cloud-minimised imagery. Subsequent LULC classification was performed in ArcGIS Pro to

maintain consistency with the desktop-based spatial analysis workflow applied in this study.

Image classification. The Landsat images were categorised into nine classes: (1) Oil Palm, (2) cropland, (3) built-up, (4) other land with tree cover or other plantation, (5) forest, (6) land clearing-oil palm plantation, (7) water bodies, (8) bare area and (9) mangrove. These classes are described in Table 2. This study employed supervised machine learning techniques based on methods proposed by Nasteski (2017). These algorithms are appropriate for generating functions that map input data to desired outputs. The functions are trained using multiple input-output examples and can classify vectors into different categories. More than 8,000 training samples were collected for each category. The RF technique is a prominent non-parametric classifier for analysing LULC change. It efficiently processes large datasets, produces precise results and improves understanding of the spatial distribution of land use and land cover (Tikuye et al., 2023).

Accuracy assessment. Map accuracy in ArcGIS Pro was assessed through the classification process. Accuracy was evaluated by generating 500 reference points using stratified random sampling. Land classes were determined based on pixel colour and field visits conducted at 327 sample points. In addition, the reference data included a 2018 map provided by LAPAN and high-resolution imagery from GEE. Various methods have been developed to assess classification accuracy, as it is useful to determine the precision of a limited number of objects before classification (Costa et al., 2018).

During the accuracy assessment, the resulting matrix summarised classification accuracy, including overall accuracy, producer's accuracy, and user's accuracy. The accuracy of RS image classification, particularly in land-cover analysis, can be measured using an error matrix (Comber et al., 2012). The column presents the user's reference values, whereas

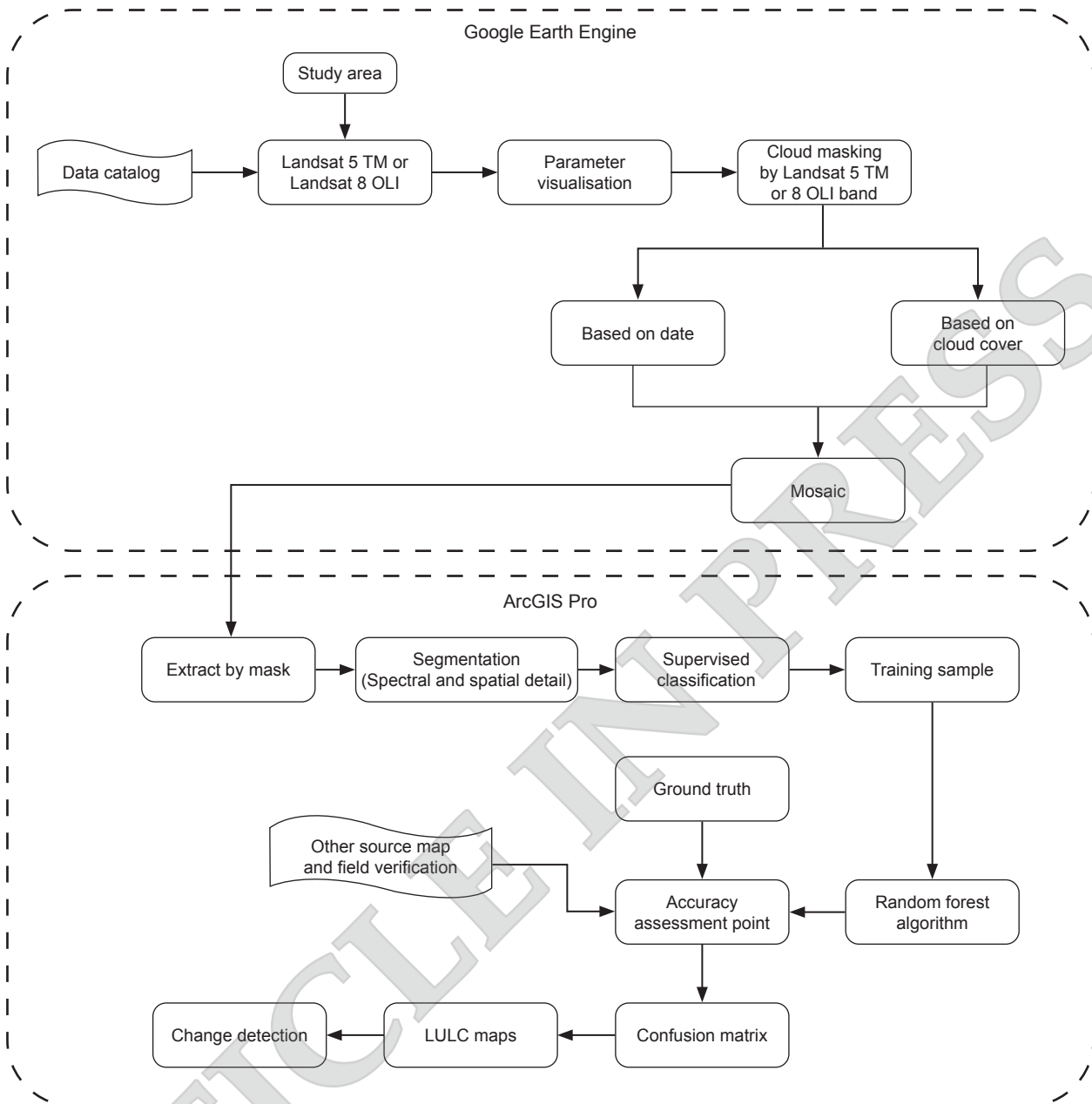


Figure 2. Research flowchart.

TABLE 2. LAND USE TYPE CLASSIFICATIONS

Class types	Description
Oil palm (OP)	Lands covered with oil palms
Cropland (CL)	Lands used for crop activity, such as paddy fields or farms
Built-up (B)	Land covered by buildings and other structures
Other land with tree cover (OL)	Lands with woody vegetation or other plantations except oil palm plantations
Forest (F)	Lands dominated by trees with a >60% canopy cover
Cleared area (CA)	Lands used for oil palm plantations without vegetation, (e.g., land clearing, replanting)
Water (W)	Rivers, lakes, reservoirs and ponds
Bare area (BA)	Lands with exposed soil, sand or rock and less than 10% vegetation cover
Mangrove (M)	Lands used for mangrove forests or swamps

Source: Anderson et al. (1976) and Food and Agriculture Organization of the United Nations (2018).

the row presents the producer's value for each class. Two types of error were identified: Omission and commission. Errors of omission and commission can result in the loss of important information, and they may not occur in the same manner. Therefore, the accuracy of both user and producer predictions was assessed separately (Stehman & Foody, 2019). User's accuracy and producer's accuracy were calculated using Equation (1) and (2), respectively. Equation (3) and (4) were used to calculate overall accuracy and the kappa coefficient.

$$\text{Producer's accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of reference pixels of the same class}} \times 100 \quad (1)$$

$$\text{User's accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of reference pixels of the same class}} \times 100 \quad (2)$$

$$\text{Overall accuracy (OA)} = \frac{\sum_{i=1}^q n_{ii}}{n} \times 100 \quad (3)$$

$$\text{Kappa coefficient (k)} = \frac{N \sum_{k=1}^r X_{kk} - \sum_{k=1}^r (X_{k+} \cdot X_{+k})}{N^2 - \sum_{k=1}^r (X_{k+} \cdot X_{+k})} \quad (4)$$

where; N is the total number of pixels; r is the number of classes; X_{kk} is the sum of pixels in row k and column k ; X_{+k} is the total samples in column k ; and X_{k+} is the total samples in row k .

Change detection. The spatial analysis Combine tool in ArcGIS Pro was used to detect land-use change. This tool interprets multiple input rasters and generates a new value for each unique combination of input values in the output raster. The output raster's attribute database includes a record of each value. Comparisons were conducted across time periods to identify changes. Single-date image processing is faster than multitemporal classification because it involves combining and classifying bands from multiple dates, seasons, or years (Langley et al., 2001; Zoungrana et al., 2015).

RESULTS AND DISCUSSION

Overall Accuracy and Kappa Coefficient

Overall accuracy and the kappa coefficient are crucial for evaluating the quality of the classification and drawing conclusions from the acquired data.

This study achieved an overall accuracy ranging from 83.30% to 89.66% across the five periods (Table 3). The calculation involved a confusion matrix, which enabled more accurate interpretation of the different land-use classifications. The kappa coefficient quantified the degree of agreement between observed and expected accuracy under random classification. The kappa values ranged from 0.79 to 0.86, which are classified as substantial to almost perfect agreement (Landis & Koch, 1977).

TABLE 3. OVERALL ACCURACY AND KAPPA COEFFICIENT

Time period	Overall accuracy	Kappa coefficient
1st	86.23	0.83
2nd	83.30	0.79
3rd	84.97	0.81
4th	87.50	0.84
5th	89.66	0.86

In addition to overall accuracy and kappa, the accuracy assessment was extended by reporting class-based metrics derived from the confusion matrix, including precision, recall and F1-score for each LULC class, as well as macro and weighted averages (Table 4). These additional criteria provide a more informative validation of classification performance, especially for imbalanced classes.

TABLE 4. PRECISION, RECALL, AND F1-SCORE FOR EACH LULC CLASS

LULC class	Precision (UA)	Recall (PA)	F1-score
Oil palm	0.941	0.894	0.917
Cropland	0.929	0.813	0.867
Built-up	1.000	0.909	0.952
Other land with tree cover	0.697	0.925	0.795
Forest	0.945	0.903	0.924
Cleared area	0.773	0.895	0.830
Water	1.000	1.000	1.000
Bare area	0.941	0.842	0.889

Note: LULC - Land use and land cover; UA - User's accuracy; PA - Producer's accuracy.

The RF algorithms are generally more accurate than other commonly used algorithms for detecting land-use change, such as SVM. RF has achieved higher overall accuracy and kappa values than SVM in previous studies. For example, RF achieved an overall accuracy of 95.2% and a kappa value of 0.87, while SVM reached 89.8% accuracy and a kappa value of 0.84 in a study conducted in Lahore (Zafar et al., 2024). Similarly, RF outperformed SVM in a study by Mutale et al. (2024), where RF achieved an accuracy rate of 96.0%, while SVM reached 77.0%.

In addition to its accuracy, RF is reliable and efficient compared with SVM, especially when handling large datasets. Therefore, it is suitable for large-area mapping (Adugna et al., 2022). RF also performs well across geomorphological settings such as plains, foothills and mountains with minimal human intervention (Tan et al., 2021).

Therefore, based on the acquired datasets, the maps produced in this study are adequate for land-use change analysis. The use of RF as a qualified classification algorithm is sufficient to support the assessment of oil palm-related land-use change. RF algorithms can be implemented to study and justify land-use changes related to oil palm, thereby informing legislation and government decision-making in Indonesia.

Land Use Changes of Barumun Watershed in Five Periods

The maps generated using supervised classification with random trees produced nine land-use classes, as shown in Table 5. In the first and second periods, forest occupied the largest share of the watershed area. Oil palm

was the second largest class, followed by other land with tree cover, bare area, cleared area for oil palm, cropland, water, built-up area, and mangrove. In the third, fourth, and fifth periods, oil palm became the largest class, followed by forest, other land with tree cover, bare area, cropland, cleared area, water, built-up area and mangrove.

These results indicate that land-use change has substantially affected oil palm plantation development in the Barumun watershed. Conversion to oil palm plantation has been documented in several studies. However, much of the available research emphasises the negative impacts of oil palm plantations and often frames oil palm as the primary cause of overall land-use change (Alfian et al., 2024; Da Silva et al., 2023; Hashim et al., 2023; Rahmawaty et al., 2022; Tarigan, 2016). Detailed information on land-use changes dynamics that clearly defines the actual sequence of conversion remains limited.

The expansion of oil palm plantations was observed in each period, as shown in Figure 3. Demand for vegetable oil continues to increase in

TABLE 5. DISTRIBUTION OF LAND USE CHANGES DURING FIVE OBSERVED PERIODS

Period	Oil palm (OP)	Cropland (CL)	Built-up (B)	Other land with tree cover or other plantation (OL)	Forest (F)	Cleared area for oil palm (CA)	Water (W)	Bare area (BA)	Mangrove (M)
Occupied area									
1st (2000–2005)	23.66%	3.33%	0.31%	21.36%	30.63%	7.72%	0.92%	11.84%	0.22%
2nd (2006–2010)	27.76%	2.68%	0.47%	20.14%	28.85%	8.11%	1.11%	10.63%	0.25%
3rd (2011–2015)	30.14%	2.82%	0.63%	18.46%	28.69%	6.83%	1.22%	10.94%	0.27%
4th (2016–2020)	33.31%	2.63%	0.49%	16.75%	27.50%	6.49%	1.21%	11.45%	0.18%
5th (2021–2023)	37.57%	2.77%	0.43%	17.78%	25.51%	4.40%	1.26%	10.12%	0.17%

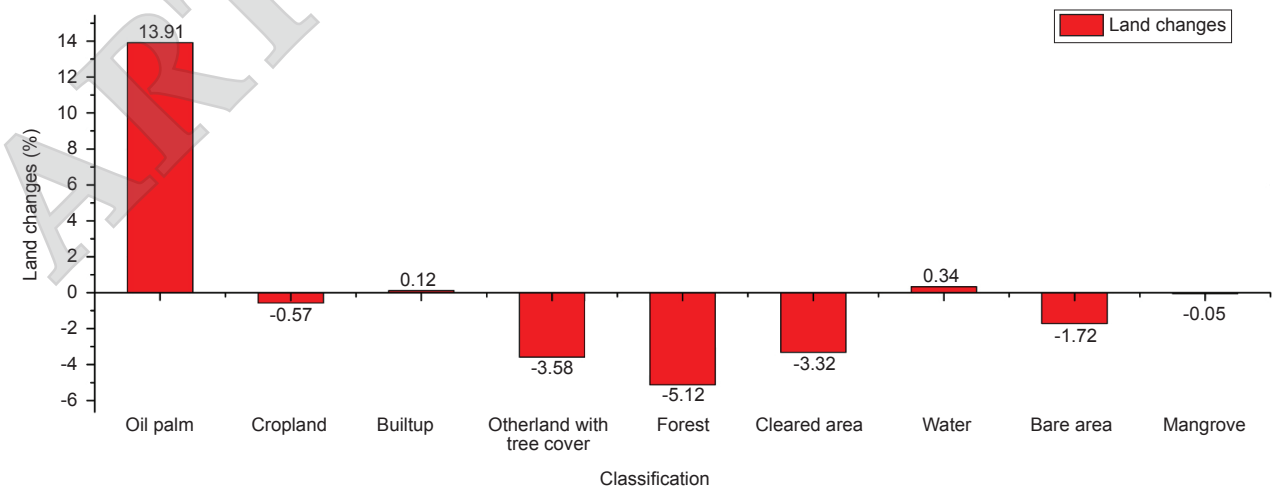


Figure 3. Percentage of land use changes over 23 years.

relation to global population growth. However, the increase in oil palm area in the Barumun watershed was primarily associated with the conversion of forests and other plantations that had previously been transformed before becoming oil palm plantations. Over the 23 years, oil palm plantations increased by 13.91%, equivalent to an average annual increase of 0.60 percentage points. Cropland decreased by 0.56% overall (0.02 percentage points per year), built-up areas increased slightly by 0.12% overall (0.005 percentage points per year), other land with tree cover decreased by 3.58% overall (0.16 percentage points per year), forests decreased by 5.12% overall (0.22 percentage points per year), areas cleared for oil palm declined by 3.32% overall (0.14 percentage points per year), water bodies increased slightly by 0.34% overall (0.01 percentage points per year), bare areas decreased by 1.72% overall (0.075 percentage points per year), and mangroves decreased slightly by 0.05% overall (0.002 percentage points per year).

The key driver of forest decline was not direct conversion to oil palm plantations, but conversion into other land uses, especially plantations or food crops. However, because various types of land were later converted to oil palm plantations, oil palm is often suspected to play a leading role in

forest clearing. In this area, forest decline occurred gradually from 2000 to 2023, although a notable decline was observed between the second and third periods. During this period, large-scale land clearing for direct oil palm expansion was limited, suggesting that future oil palm development often occurred on land that had already been opened for other uses.

As shown in *Figure 4*, the results indicate that other plantations or crops contributed most significantly to the establishment of oil palm plantations. During the first transition period, this class contributed 88,814.97 ha and remained the dominant source of oil palm expansion in subsequent periods. This pattern indicates a gradual shift toward oil palm plantation establishment, which continues to be perceived as a profitable commodity and business opportunity (Ayompe et al., 2021; Pye, 2019; Wardhani & Rahadian, 2021).

The transitional pathway from forest to other land with tree cover and subsequently to oil palm also reflects socio-economic decision-making in the watershed. For many landholders, intermediate tree crops or mixed plantations may function as a lower-risk stage after forest clearing because they provide flexible land management options before a permanent commodity choice

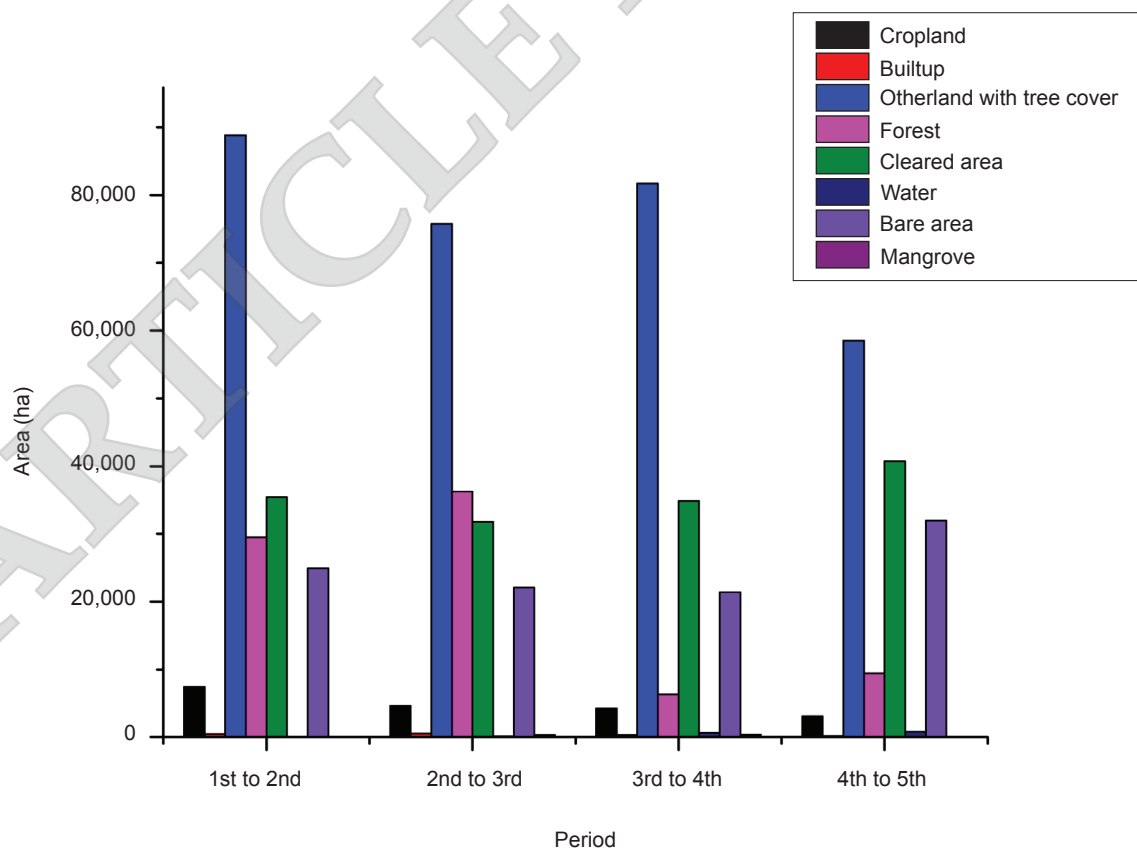


Figure 4. Other land use changes prior to changes to oil palm plantation.

is made. Oil palm then becomes attractive when farmers and investors perceive stronger and more stable market opportunities, better processing infrastructure and clearer integration into regional supply chains than alternative crops. In North Sumatra, oil palm is already a major livelihood crop, and smallholder agribusiness sustainability in Labuhan Batu is closely tied to plantation income (Suardi et al., 2022). This socio-economic context is consistent with previous findings that oil palm expansion in Indonesia is shaped not only by biophysical suitability but also by policies, land tenure, market incentives and farmer livelihood strategies (Dharmawan et al., 2020; Gatto et al., 2015). Therefore, the forest-other tree crops-oil palm sequence should be interpreted not simply as a spectral land-cover pattern, but as a staged land-use strategy in which households and plantation actors respond to commodity profitability, land availability, and institutional conditions. Grounding the geospatial results in these livelihood and market realities strengthens the conclusion that oil palm expansion in the Barumun watershed is largely an indirect land-use change process rather than a single-step conversion from forest.

Previous studies show that a substantial portion of deforestation is attributed to the expansion of commercial cropland, pastures, and tree plantations. Key commodities linked to deforestation include cattle meat, forestry products, oil palm, cereals and soybeans. This trend is particularly pronounced in tropical and subtropical regions, where international demand for these commodities is high (Pendrill et al., 2019). The trade of forest-risk commodities plays a critical role in deforestation. Countries with increasing forest cover often import commodities that contribute to deforestation elsewhere, thereby complicating efforts to achieve a global forest transition (Leblois et al., 2017). This study contributes to the evidence that land-use change in the Barumun watershed was not driven primarily by direct conversion to oil palm plantations.

Nevertheless, some forest areas were converted directly into oil palm plantations. The most significant direct conversion occurred during the second period. A subsequent decrease may be associated with sustainable palm oil regulations, such as the Indonesian Sustainable Palm Oil (ISPO) policy introduced in 2011 and the 2018 government moratorium on oil palm plantation expansion.

CONCLUSION

Over 23 years, land utilisation in the Barumun watershed changed substantially. Given the potential for economic growth and rising demand

for vegetable oil, oil palm plantation development is likely to remain an important land-use pressure. However, land-use change in the Barumun watershed did not occur primarily through direct conversion to oil palm plantation. Instead, the dominant pathway involved prior conversion to other land with tree cover or other plantations, which contributed 47.6% in the first-to-second period, 44.2% in the second-to-third period, 54.6% in the third-to-fourth period and 40.4% in the fourth-to-fifth period. Land-use and management strategies are therefore needed to ensure sustainable and efficient development in accordance with social, economic and environmental needs. This land-use change study is important for spatial planning because it clarifies how an area is developing, which factors influence land-use change and how future policies can be designed. Future research should integrate higher-resolution imagery, statistically analyse socio-economic drivers, model future change scenarios and apply the methodology to other watersheds.

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