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Spatial Dynamics of Land Cover Change in the Ngata Toro Customary Forest, Toro Village, Kulawi District, Sigi Regency, from 2021 to 2025

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Abstract: Customary forests play a crucial role in maintaining ecosystem balance, biodiversity, and the sociocultural sustainability of local communities. However, pressure on forest cover continues to increase due to land clearing and conversion. This study was conducted from February to July 2025 in the Ngata Toro Customary Forest, Toro Village, Kulawi District, Sigi Regency, to analyze land cover changes from 2021 to 2025 using satellite imagery and the Object-Based Image Analysis (OBIA) segmentation method. The results show a decrease in forest area from 1,604.16 ha (2021) to 1,475.98 ha (2025), or a decrease of approximately 128.18 ha (7.99%), accompanied by an increase in non-forest area from 140.99 ha to 268.88 ha. Initial changes occurred in high-access areas near settlements and roads, then spread inland, leading to forest fragmentation. Peak deforestation occurred in 2024, with a decrease of 57.49 ha in one year. Spatial patterns show a close relationship between deforestation and accessibility, topography, and agricultural intensification. Classification accuracy tests yielded an overall accuracy of 80–85%, with the highest in 2021 and the lowest in 2023. Fragmentation reduces habitat connectivity, threatens wide-ranging species, and degrades ecosystem functions such as carbon storage and hydrological regulation. These results underscore the importance of ecosystem-based management strategies and controlled land clearing to maintain the ecological integrity of customary forests.

Keywords: Deforestation; Forest fragmentation; Land cover; OBIA; Satellite imagery

Introduction

A National Park is a Nature Conservation Area containing a native ecosystem, managed using a zoning system, and utilized for research, science, education, cultivation support, and environmental utilization as stipulated in Law Number 32 of 2024 (Reilly et al., 2022). Lore Lindu National Park (TN Lore Lindu) is a National Park located in Central Sulawesi Province and was established in 1999. The area is surrounded by 72 buffer villages inhabited by several indigenous communities, one of which is the To Kulawi Moma Indigenous Law Community (MHA) in Ngata Toro. This area has been traditionally protected by the indigenous community through local wisdom and a customary law-based management system (Trialfhianty et al., 2025; Handayani et al., 2023). The establishment of the Ngata Toro Customary Forest in 2021, covering an area of 1,744.2 hectares and entirely within the Lore Lindu National Park area, demonstrates legal recognition of the role of indigenous communities in conservation area management (Lumosi et al., 2025; Mansuy et al., 2023).

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This recognition also brings new challenges regarding the alignment of customary land functions with conservation principles applied in national parks (Ferretti-Gallon et al., 2021). In this context, it is crucial to ensure that the change in management status from the state to indigenous communities does not result in a deviation from the ecological function of the forest area.

The establishment of the Ngata Toro Customary Forest represents a customary law-based management model that considers the welfare of local communities and can be effectively integrated into the national development framework (Lanini et al., 2018; Fatem et al., 2018). According to Sukarsih et al. (2021), Sinner et al. (2022), the Kajang Customary Law Community (MHA) divides the forest area into three zones: borong karamaka (sacred forest), borong batasayya (border forest, where timber may be harvested with the permission of customary leaders), and borong luara (community forest, managed by the community for agricultural production). Based on the principles of common property rights (Baird et al., 2025; Agrawal & Gibson, 1999), the success of collective natural resource management is determined by clear boundaries, access rights, oversight, sanctions, and institutional recognition. Strengthening MHA institutions is a key prerequisite for maintaining the alignment of customary forest functions with customary spatial patterns, namely pangale (protection zone), wanangkik (restricted zone), wana (management zone), and oma (settlement and agricultural zone) (Eckert et al., 2025; Golar et al., 2023).

However, land use dynamics inconsistent with customary zoning can pose a risk of forest degradation and conflicts of interest, as occurred in the Tarok Nagari region of West Sumatra, due to weak customary oversight of spatial use (Oktavia & Suparwoko, 2022). Therefore, the management of the Ngata Toro Customary Forest needs to consider ecological sustainability while ensuring that land rights are not abused, particularly since customary forest status prohibits alienation (the sale or transfer of land) (Mahendra et al., 2024). The government's role as regulator remains essential to ensure mentoring, institutional strengthening, and collaboration between stakeholders to maintain land cover sustainability and the suitability of forest functions (Widiyanto et al., 2025; Siahaan et al., 2025). This collaboration must be sustainable so that conservation goals and the welfare of indigenous communities can align within a sustainable development framework (Febrina et al., 2021; Pratiwi et al., 2019).

Based on the above background, a more in-depth study is needed to examine the spatial dynamics of land cover in the Ngata Toro Customary Forest, assess the suitability of forest functions with customary zoning, and evaluate the extent to which management by the To Kulawi Moma Customary Community can maintain the area's ecological function and ensure spatial use is in accordance with customary spatial planning principles. The results of this study are expected to provide policy recommendations for strengthening customary institutions and developing a collaborative model for sustainable forest management.

Method

Research Location

This research was conducted over six months, from February to July 2025, in the Ngata Toro Customary Forest area, Toro Village, Kulawi District, Sigi Regency (Figure 1).

The Ngata Toro Customary Forest has five land cover classes and is dominated by secondary dryland forest. Geographically, the Ngata Toro Customary Forest is located at coordinates 120°00′55″–120°04′35″ East Longitude and 1°28′53″–1°32′43″ South Latitude. The tools used in this study included a Global Positioning System (GPS) to capture coordinate points, a laptop with ArcGIS Pro software, a mobile phone equipped with the SIMRELI application, stationery, and a camera.

The materials used in this study consisted of primary data, namely field coordinate data obtained directly using the SIMRELI application, and interview and direct observation data at specific points to ensure the accuracy of the classification.

Meanwhile, secondary data included the Ngata Toro Customary Forest Map at a scale of 1:50,000, Decree Number SK.5679/MENLHK-PSKL/PKTHA/PSL.1/9/2021, dated September 10, 2021, concerning the Determination of the Ngata Toro Customary Forest for the To Kulawi Moma Customary Community in Ngata Toro, covering an area of approximately 1,747 hectares; Sentinel-2 satellite imagery from the Copernicus Open Access Hub covering the period July 2021–July 2025; Google Earth satellite imagery; and the 2023 Indonesian Earth Map at a scale of 1:25,000. Additionally, village and sub-district administrative boundaries were obtained from the Geospatial Information Agency (BIG).

Data Analysis Techniques

In general, the research was conducted in several stages: image pre-processing, object-based segmentation, image classification, field verification, and accuracy testing. The pre-processing stage involved preparing tools and materials.

Image Preprocessing

Image preprocessing is a crucial initial stage in preparing satellite image data prior to further analysis. This stage aims to improve data quality by eliminating geometric and radiometric distortions, reducing artifacts or noise, and ensuring the suitability of the coordinate system used. This process includes activities such as importing data into image processing software, creating composite bands (band combination) to produce displays with specific channel combinations such as natural RGB or false color, image sharpening to enhance spatial detail, image cropping to suit the study area, and coordinate transformation to align the image with the desired map projection (Cardille et al., 2024).

Object-Based Segmentation (OBIA)

Object-Based Segmentation, or Object-Based Image Analysis (OBIA), is a method that breaks down an image into homogeneous segments based on spectral, shape, and texture similarities. This process is generally performed using multiresolution segmentation techniques with parameters such as scale to determine object size, color to measure spectral uniformity, shape to consider geometric factors, and compactness or smoothness to adjust the smoothness and density of polygon shapes. The OBIA approach has several advantages over single-pixel-based methods, including its ability to contextually combine spectral and spatial information, reduce errors caused by noise and mixed pixels, and produce more accurate classifications for medium- to high-resolution imagery. Recent studies have shown that OBIA is even more effective when integrated with deep learning techniques such as CNNs for classifying complex objects.

Image Classification

Image classification is the process of grouping segmented segments, or pixels, into specific classes that represent land cover and land use. One method used in this study is Maximum Likelihood Classification (MLC), a supervised classification approach that assumes that each land cover class has a predictable spectral statistical distribution. The classification process begins with determining the training area based on reference data or field observations, followed by calculating spectral statistics for each class, and finally, assigning classes to all images based on the probability of spectral value similarity. Although MLC is widely used due to its consistency and ability to produce relatively high accuracy on multispectral imagery, recent studies have shown that machine learning-based algorithms such as Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) often produce better accuracy, especially on high-resolution imagery.

Field Survey (Ground Check)

Field surveys, or ground checks, are conducted as a validation step for image classification results. This activity involves randomly or systematically sampling coordinate points using GPS, recording land cover types at the location, and ensuring that all classified classes are represented in the sample. The obtained ground truth data serves as a crucial reference in the classification accuracy evaluation process. Therefore, the quality and distribution of samples in the field will significantly impact the reliability of the analysis results.

Accuracy Testing

Accuracy testing aims to measure the degree to which image classification results match actual conditions in the field. The method used is a Confusion Matrix or error matrix, which allows the calculation of various indicators such as Overall Accuracy (OA), Kappa Coefficient, User's Accuracy, and Producer's Accuracy. In recent research, validation techniques such as k-fold cross-validation are widely used to improve the reliability of evaluation results. In general, classifications with an overall accuracy of ≥ 80% are categorized as excellent, 60–79% as good, and <60% as poor. Accuracy calculations are performed by comparing the analysis results with the results of field checks. The accuracy test aims to identify analysis errors so that the accuracy percentage can be determined. Commission errors are classification errors in the form of an excess number of pixels in one class due to the inclusion of pixels from another class. The level of mapping accuracy is determined using a classification accuracy test with the formula.

$$Kappa\ Accuracy = \frac{(N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r} Xi + X + 1)}{(N^2 - \sum_{i=1}^{r} Xi + X + i\,)} \times 100\% \quad (1)$$

$$User's\ Accuracy = \frac{Xii}{X+i} \times 100\% \quad (2)$$

$$Producer's\ Accuracy = \frac{Xii}{Xi+} \times 100\% \quad (3)$$

$$Overall\ Accuracy = \frac{\sum_{i=2}^{r} Xii}{N} \times 100\% \quad (4)$$

Information:
N: Number of pixels in the sample
Xi+: Number of pixels in the i-th row
X+i: Number of pixels in the i-th column
Xii: Diagonal value of the i-th row and i-th column of the contingency matrix

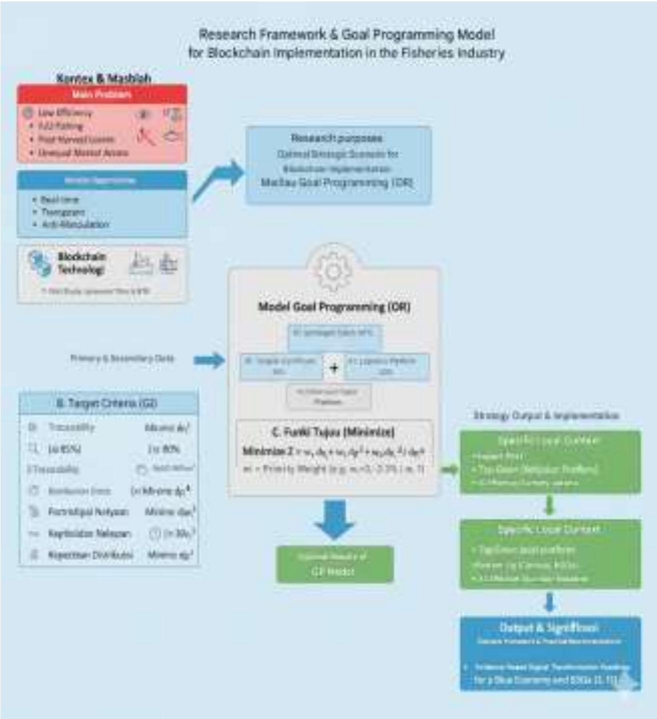

Figure 1. Schematic diagram of this research method

Results and Discussion

Based on satellite image analysis and land cover classification, significant changes in forest cover in the Ngata Toro Customary Territory have been observed over the past five years.

2021

2021 was the starting point for observations, with forest cover still dominating the area, covering 1,604.16 hectares. Non-forest areas covered only 140.99 hectares and were scattered sparsely along the outskirts (Figure 2). The distribution of non-forest areas was primarily concentrated around roads and the boundaries of customary settlements. Satellite imagery showed relatively intact vegetation, dominated by deep green, indicating a dense and relatively undisturbed forest canopy. Overall, the condition of the area in this year can be categorized as stable, with low land use pressure. Ecologically, the dominant forest cover in 2021 indicates that the region still maintains high ecosystem integrity. Even canopy density and minimal fragmentation indicate low levels of anthropogenic disturbance, allowing optimal ecological functions such as carbon sequestration, soil protection, and wildlife habitat (Almeida et al., 2019). Furthermore, limited physical access to the interior of the area—reflected by the concentration of non-forested areas around transportation routes and settlement boundaries—provides natural protection against large-scale land clearing (Barber et al., 2014). Therefore, these initial conditions serve as an important benchmark for monitoring the rate of land cover change and its impact on the sustainability of the indigenous forest ecosystem in subsequent years.

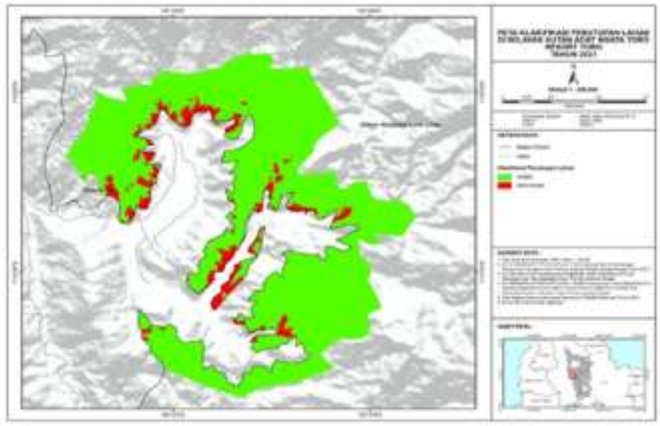

Figure 2. Land cover classification map in the Ngata Toro Customary Forest Area, Toro Resort, 2021

2022

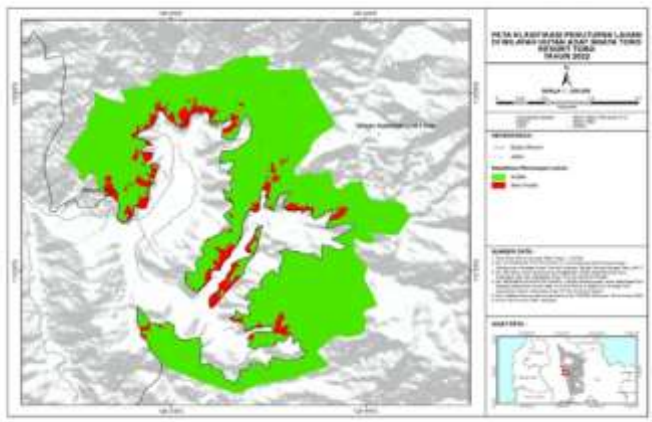

Figure 3. Land cover classification map of the Ngata Toro Customary Forest Area, Toro Resort, 2022

Entering 2022, there was a slight decrease in forest area to 1.602.74 hectares, while non-forest area increased to 142.12 hectares (Figure 3). Although the difference in change was not significant, the classification map shows a gradual expansion of non-forest areas in the northern and western parts of the region. The red color on the classification map begins to show small fragmentations in several new points, indicating the onset of land clearing activities. This deforestation process remains under control but warrants caution, as it indicates the potential for the expansion of community land use. The small changes that occurred in 2022, with a decrease in forest area to 1.602.74 hectares and an increase in non-forest area to 142.12 hectares, indicate the beginning of a limited-scale land conversion process. Spatially, this pattern indicates the initial expansion of non-forest areas in highly accessible areas, such as the northern and western parts of the region. According to Engert et al. (2025), the initial phase of deforestation generally begins with land clearing at the forest edge adjacent to transportation infrastructure, followed by gradual fragmentation toward the interior. This situation requires early protection efforts because, even if the changes are relatively small, their cumulative effects can accelerate habitat degradation and reduce biodiversity.

2023

2023 marked the initial phase of a significant increase in land conversion. Forest area decreased to 1.565.73 hectares, while non-forest area increased sharply to 179.14 hectares (Figure 4). Satellite imagery and the classification map clearly demonstrate the increasingly even distribution of non-forest areas, particularly in the northern, central, and southern parts of the area. Land clearing activities appear to be expanding around high-access zones, such as roads and near the outer boundaries of the area (Spencer et al., 2023; Syaban & Appiah-Opoku, 2024). This pattern indicates increasing pressure on land use for activities such as farming, gardens, or other uses by the surrounding community. In 2023, land conversion increased significantly, with forest area decreasing to 1.565.73 hectares and non-forest area increasing to 179.14 hectares. This more even distribution of land cover across the area indicates that pressure on forests has expanded from the periphery to the interior. Increased accessibility through secondary routes accelerates fragmentation and triggers a cycle of ecosystem degradation, where the resulting open areas are more vulnerable to invasion by non-endemic species and further conversion for agriculture and settlements.

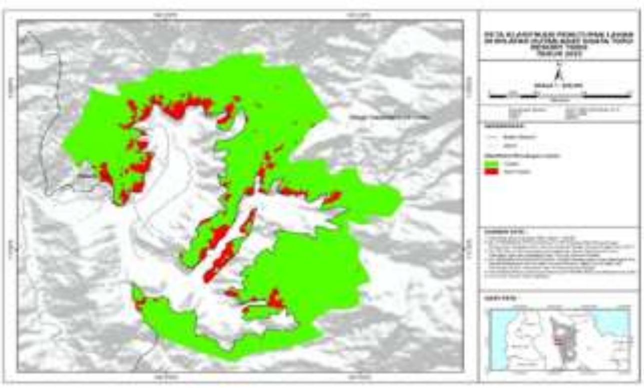

Figure 4. Land cover classification map in the Ngata Toro Customary Forest Area, Toro Resort, 2023

2024

A striking change occurred in 2024, with forest area decreasing again to 1,508.24 hectares, and non-forest area increasing significantly to 236.62 hectares (Figure 5). Satellite imagery shows the emergence of large new open areas in the north and southwest of the area. The land cover classification map shows an increase in the number and extent of red patches, indicating a more extensive conversion of forest land to non-forest land. This year showed a significant spike in deforestation compared to previous years, indicating more intensive land use activities. The year 2024 marked a significant spike in deforestation. Forest area decreased to 1,508.24 hectares, while non-forest area increased to 236.62 hectares. Satellite imagery identified large patches of open areas, particularly in the north and southwest, indicating larger-scale land clearing (Kunte & Bhat, 2024; Driscoll et al., 2025), which show that increased deforestation is typically associated with intensified land use, both for commercial agriculture and other uses, thereby reducing forests' capacity to store carbon and maintain the hydrological cycle. The ecological impacts include not only the loss of vegetation cover but also the disruption of ecosystem functions that support the lives of local communities.

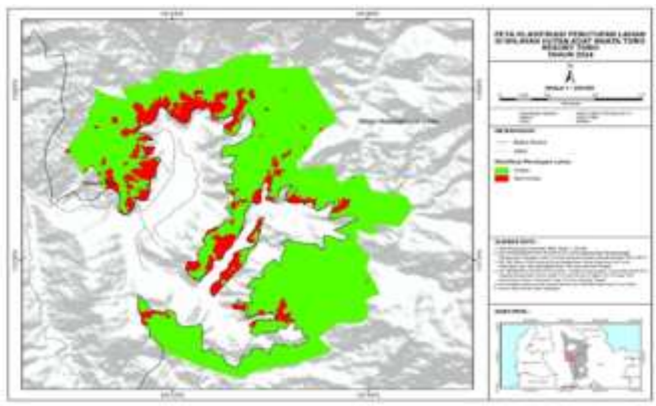

Figure 5. Land cover classification map in the Ngata Toro Customary Forest Area, Toro Resort, 2024

2025

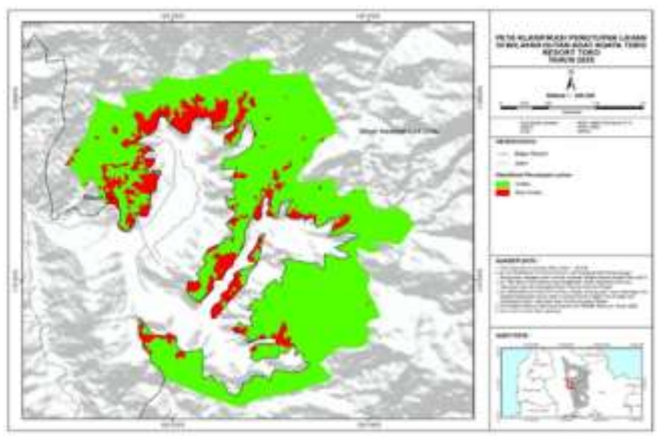

Figure 6. Land cover classification map in the Ngata Toro Customary Forest Area, Toro Resort, 2025

Spatial analysis of the 2025 land cover classification map in the Ngata Toro Customary Forest Area shows significant changes in land cover composition over the past five years. Based on the classification results, forest area in 2025 was recorded at 1.475.98 hectares, while non-forest area reached 268.88 hectares (Figure 6). This data indicates a decrease in forest cover of 32.26 hectares, or approximately 2.14%, compared to 2024, accompanied by an increase in non-forest area of 32.26 hectares during the same period. The map shows that non-forest areas (marked in red) are not randomly distributed but follow a specific pattern closely related to accessibility and topography. The distribution of non-forest areas is most dominant in locations directly adjacent to settlements, thus becoming the primary starting point for land conversion. Furthermore, the distribution of land cover changes indicates the fragmentation of forest blocks into small patches. This fragmentation has the potential to reduce habitat connectivity, which could negatively impact the survival of species that require large roaming spaces. The linear and diffuse pattern following slope contours and road access indicates that land clearing was likely carried out in stages, exploiting ease of access. This aligns with previous research findings that accessibility is a major driver of deforestation in customary forest areas (Angelsen, 2010; Barber et al., 2014). This finding is also relevant to research by Alamgir et al. (2019) and Haddad et al. (2015), which stated that infrastructure development and ease of access are key drivers of forest fragmentation, reducing habitat connectivity and increasing the risk of loss of species that require large roaming spaces. The fragmentation identified in 2025 is a critical indicator that customary forest areas require ecosystem-based management strategies to maintain their ecological integrity.

Accuracy Testing

Testing the accuracy of image processing results is necessary to produce information that reflects the expected conditions. This process is carried out due to the potential for errors in the previous process, which can cause existing information to become less reliable (Adrita et al., 2021; Pfeiffer et al., 2025). The calculated value is the diagonal value where each data matrix intersects, which is then entered into the Overall Accuracy (OA) calculation formula. The maximum OA value is 100%, and the closer the value is to the maximum, the more accurate the classification results are (Suni et al., 2023).

Table 1. Accuracy Test Results

	Year	2021		2022		2023		2024		2025					
Year	Land Class	F	NF	F	NF	F	NF	F	NF	F	NF	Column	Producer	User	Overall
	F	8	1	0	1	0	0	0	0	0	0	10	88.89	80	85
2021	NF	1	9	0	0	0	0	0	0	0	0	10	90	90	
	F	0	0	8	0	0	1	0	1	0	0	10	81.82	80	85
2022	NF	0	0	0	9	1	0	0	0	0	0	10	81.82	90	
	F	0	0	0	1	8	1	0	0	0	0	10	80	80	80
2023	NF	0	0	0	0	1	8	0	1	0	0	10	72.73	80	
	F	0	0	1	0	0	0	8	0	0	0	10	80	80	85
2024	NF	0	0	0	0	0	1	0	9	0	0	10	81.82	90	
	F	0	0	0	0	0	0	0	0	8	2	10	72.73	80	85
2025	NF	0	0	0	0	0	0	0	0	1	9	10	81.82	90	
Rows Total		9	10	9	11	10	11	10	11	11	11	150			

Information: F = Forest; NF = Non-forest

Based on the accuracy test results in Table 1, the overall accuracy for land cover classification for the 2021–2025 period ranged from 80–85%, indicating a good level of classification reliability according to thematic map accuracy (Congalton & Green, 2019). The years 2021, 2022, 2024, and 2025 each achieved an overall accuracy of 85%, while 2023 showed the lowest value at 80%. This variation indicates that classification quality is relatively consistent, although there are slight decreases in certain years, likely influenced by spectral similarities between forest and non-forest classes in transition or edge areas (Yu et al., 2024; Sovann et al., 2025). Producer accuracy values for the forest class ranged from 72.73% to 88.89%, with the highest value in 2021, indicating that most forest areas were correctly identified in that year. However, the decrease to 72.73% in 2023 and 2025 indicates significant omission errors, with some forest areas being classified as non-forest. For the non-forest class, producer accuracy remained relatively stable at around 80–90%, indicating the system's ability to detect non-forest areas.

Meanwhile, user accuracy for the forest class hovered around 80%, indicating commission errors due to some non-forest pixels being classified as forest. For the non-forest class, user accuracy reached 90% in 2021, 2022, and 2025, indicating a high level of user confidence in the classification results for this category. In general, the accuracy obtained meets the feasibility threshold for medium-term land cover change analysis, but improving pre-processing methods, adding training sample data, and applying object-based segmentation algorithms could further enhance accuracy, especially in transition areas between forest and non-forest (Maxwell et al., 2018; Belgiu & Drăguț, 2016).

Conclusion

An analysis of land cover dynamics in the Ngata Toro Customary Forest Area during the 2021–2025 period shows a consistent decline in forest area from 1,604.16 hectares to 1,475.98 hectares, a decrease of approximately 128.18 hectares. This decline is accompanied by a significant annual increase in non-forest area, with changes concentrated in high-access areas such as near settlements, roads, and area boundaries. The distribution of non-forest areas tends to follow access routes and slope contours, indicating a gradual but widespread land conversion process. The fragmentation of forest blocks into small plots is increasingly clearly identified on the latest classification map, potentially reducing habitat connectivity and threatening the survival of species that require extensive roaming space. These findings reinforce the hypothesis that accessibility is a major driver of deforestation in customary forest areas. If this trend is not addressed through effective management and monitoring, the ecological function, landscape integrity, and role of customary forests as support systems for community livelihoods and biodiversity habitats will be increasingly threatened. The 2021–2025 land cover classification shows good accuracy (80–85%) and consistency, with more stable performance in non-forest classes than in forest classes. While suitable for medium-term analysis, precision, especially in transition areas, could be improved through pre-processing optimization, additional training samples, and object-based segmentation.

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Author Contributions
Conceptualization; methodology.; C. A. M.; validation; formal analysis; I. R.; investigation; A. M.; resources; G; data curation: writing—original draft preparation; writing—review and editing.; S. D. M.; visualization: A. S. M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest.

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