

Spatial Model of Forest Cover Change using Moisture Index in Kolaka Regency

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Abstract

Kolaka Regency plays a crucial role, both ecologically and economically. This study aims to identify long-term changes in forest cover using the Moisture Index, using a collection of Landsat satellite imagery. Forest cover is defined by a threshold: values >0.7 are considered forest cover, while values <0.7 are considered non-forest areas. Forest cover in Kolaka Regency fluctuates. The 2000-2005 period saw the sharpest decline, reaching an unmitigated loss of 404.00 km². Although forest cover recovered in subsequent years, it accounted for only a third of the total forest loss, reaching 462.31 km². Extractive mining activities and land conversion drive forest loss in this region. A comparison of protected forest areas and the rate of forest loss indicates that legal protection does not automatically guarantee the presence of vegetation cover in the field. Therefore, forest management in Kolaka must shift from an administrative approach to a spatially based, real-time monitoring approach.

Keywords: Forest Cover; Kolaka Regency; Normalized Difference Moisture Index; Remote Sensing.

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Introduction

Southeast Sulawesi is a province in the Sulawesi archipelago with the third-highest population, at 9,563 people. However, this province has the highest population growth rate, at 1.65% per year (Badan Pusat Statistik, 2025a). This high growth rate, if not managed properly, can put serious pressure on the environmental carrying capacity. Forests in Sulawesi are reported to continue shrinking under significant pressure, even reaching the edges of protected areas. Sulawesi ranks third after Sumatra and Kalimantan with a forest loss rate of 91,500 ha/year (Santoro et al., 2025). Therefore, the Southeast Sulawesi government continues to conserve biodiversity by monitoring protected areas across its territory. This province has a protected area of 111,756,560 ha, and

Nature Reserves and Nature Conservation of 40,707,750 ha (Badan Pusat Statistik, 2025b). Nevertheless, this region requires continuous monitoring to ensure proper forest management. Accurate and reliable forest cover maps play a crucial role in forestry planning, monitoring forest degradation, and developing forest policy and management plans (Tariq et al., 2023).

In Indonesia, the history of forest management is deeply rooted in the Dutch colonial regime, which implemented the Domein Verklaring principle—declaring forest areas as state property primarily for commodity exploitation (Berenschot & Dhiaulhaq, 2025). This highly centralized legacy historically alienated local communities from their traditional living spaces, inadvertently fostering a long-term perception of forests as state-owned

resources that could be freely exploited without sustainability constraints (Bose, 2023). To mitigate the resulting environmental degradation and ongoing social conflicts, the Indonesian government has progressively shifted its paradigm toward collaborative forest management. Formally operationalized through the Social Forestry program, this approach grants legal access rights and management responsibilities to local actors to equitably distribute benefits, foster local stewardship, and optimize conservation performance (Gunawan et al., 2024; Rakatama & Pandit, 2020). Within this collaborative framework, various technical measures are actively deployed to maintain maximum canopy cover and support natural regeneration in highly vulnerable landscapes. These include developing enrichment plantings, enforcing ecosystem restoration, and establishing robust buffer zones around core conservation areas to systematically reduce community dependence on timber extraction while sustainably improving local livelihoods (de Souza et al., 2025).

Remote sensing has become a key alternative for analyzing forest cover changes over the past several years. Numerous methods have been developed to evaluate vegetation and forests. Among various spectral indicators, the Normalized Difference Moisture Index (NDMI) has emerged as one of the most robust and widely adopted frameworks for dense canopy monitoring (Schultz et al., 2018; Shimizu et al., 2019). The deployment of such remote sensing indices is increasingly critical, given that conventional field-based inventory methods are notoriously time-consuming, labor-intensive, and inherently prone to generating outdated baselines in today's rapidly transforming environments (Dragomir et al., 2025). By contrast, NDMI-driven forest monitoring systems leverage advanced sensor capabilities to effectively capture complex land-cover heterogeneities and structural canopy

variations. Because it responds directly to cellular water retention rather than superficial greenness, this index is highly sensitive to subtle, long-term degradation trajectories while remaining immensely cost-effective (Nguyen et al., 2025). Therefore, this study aims to identify long-term changes in forest cover, compare local modeling results with Global Forest Watch (GFW) data, and conduct an overlay analysis of land-cover types and forest-area functions. This is done to evaluate the effectiveness of legal protection status in reducing on-the-ground degradation rates, identify area-specific drivers of deforestation, and formulate more targeted collaborative management strategies.

Materials and Methods

Study area

This research was conducted in Kolaka Regency, which is geographically located at 3°36' – 4°35' South Latitude and 120°45' – 121°52' East Longitude, and spatially located at UTM Zone 51S coordinates using the WGS 84 datum (Figure 1). Kolaka Regency has an area of 2,958.55 km². On the east side is a mountainous forest that borders East Kolaka Regency and North Kolaka Regency, with relatively steep terrain, while the coastal area is on the west side, bordering Bone Bay. This area consists of mountains and hills that stretch from north to south, and it has several rivers that provide energy for industrial and household needs, as well as for irrigation and tourism. Kolaka Regency has a strategic position with relatively high mobility and economic activity. The population of Kolaka Regency in 2024 was 257,733 people.

Type and Source of Data

This study uses a remote sensing approach based on Landsat satellite imagery to analyze forest cover dynamics for the period 1990–2025. The primary data used are Landsat Surface Reflectance (SR)

imagery, accessed and processed via the Google Earth Engine (GEE) platform. GEE is a cloud-based computing platform that enables efficient and consistent processing of large-scale geospatial data (Aldiansyah & Saputra, 2023). The datasets used include 5 TM images from before 2015, Landsat 8 Operational Land Imager (OLI) data for

2020, and Landsat 9 OLI data for 2025. The Landsat program was chosen because it has a long-term data archive, 30-meter spatial resolution, and radiometric consistency, which support multi-temporal land-cover change analysis (Demarquet et al., 2023; Donatien et al., 2024). The details of the data used are presented in Table 1.

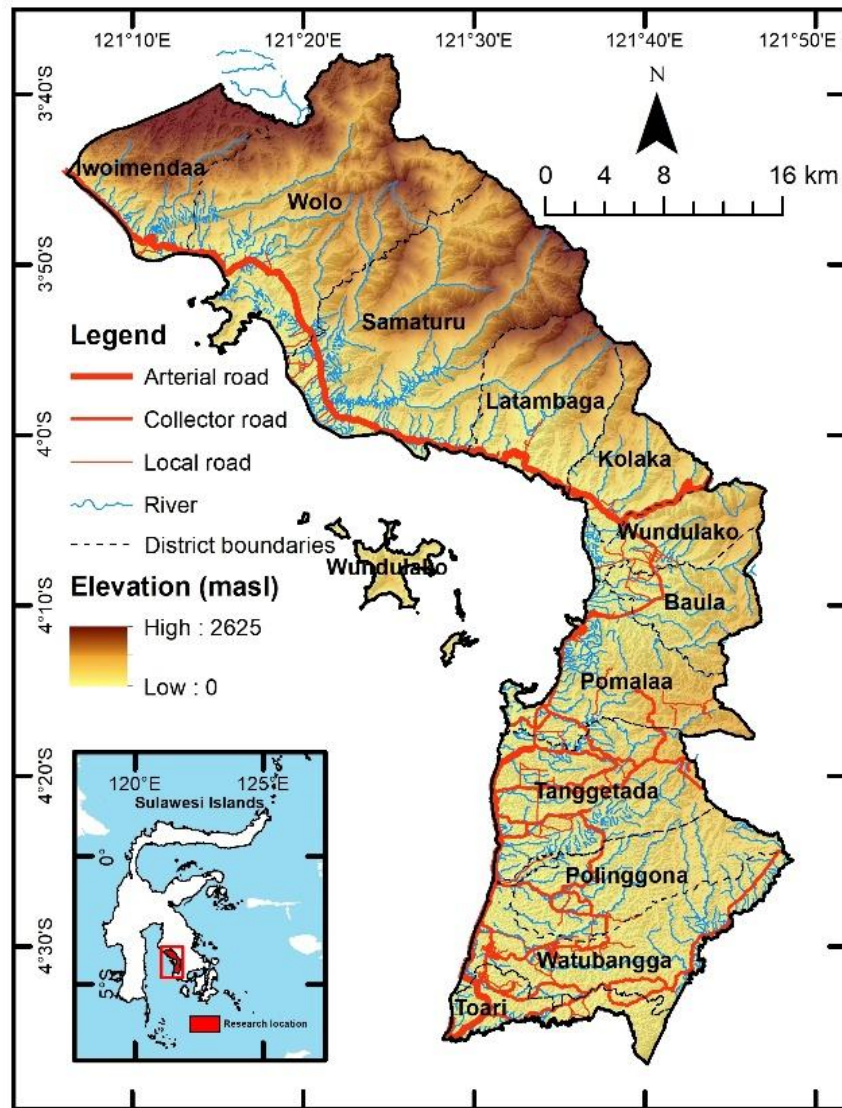


Figure 1. Research Location in Kolaka Regency.

Table 1. Types of satellites used.

Satellite	Sensor	Path/Row	Year	Resolution	Atmospheric correction	Data source
Landsat 5	TM	113/63	1990	30	LEDAPS	USGS
Landsat 5	TM	113/63	1995	30	LEDAPS	USGS
Landsat 5	TM	113/63	2000	30	LEDAPS	USGS
Landsat 5	TM	113/63	2005	30	LEDAPS	USGS
Landsat 5	TM	113/63	2010	30	LEDAPS	USGS
Landsat 5	TM	113/63	2015	30	LEDAPS	USGS
Landsat 8	OLI	113/63	2020	30	LaSRC	USGS
Landsat 9	OLI-2	113/63	2025	30	LaSRC	USGS

Data Collection and Processing

Data collection was conducted using temporal and spatial filtering techniques on USGS Landsat Level-2, Collection 2, Tier 1 image collection at GEE. Temporal filtering was performed by constructing image composites for each target year using three years (year-1 to year+1). To avoid phenological bias and maintain strict interannual consistency, image acquisition was restricted to identical seasonal windows (dry-season months) across all target periods. This approach aims to increase the number of observations and reduce data gaps due to cloud cover, resulting in a more stable representation of annual conditions. Spatial filtering was performed by restricting the imagery to the study area using the boundary filter function. This combination of filters ensured that only temporally and spatially relevant imagery was further processed.

The data processing stage began with cloud and cloud shadow correction (cloud masking) using the pixel quality band (QA_PIXEL) in the Surface Reflectance product. Masking was performed using a bitwise method to remove pixels indicated by clouds, dilated clouds, cloud shadows, and cirrus (specifically for Landsat 8–9). This procedure is crucial for minimizing spectral bias due to atmospheric contamination and improving the accuracy of surface information extraction (Singh et al., 2025). Reflectance values were then converted from digital number scale to surface reflectance using the official Landsat Collection 2 scale factor. Next, cloud-cleared images were composited using the median method for each target year period. The median composite was chosen because it is relatively robust to extreme values and cloud residuals compared to the mean method (Aldiansyah & Saputra, 2023).

Data Analysis

Forest cover analysis was conducted using the Normalized Difference Moisture Index (NDMI), a normalized difference-based spectral index that utilizes the Near-Infrared (NIR) and Shortwave Infrared (SWIR) channels. The NDMI was selected conceptually to distinguish dense, intact forest structures from open or degraded land due to its high sensitivity to vegetation water content, canopy stratification, and cellular leaf structure. This index is calculated using the following equation (Schultz et al., 2018):

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad (1)$$

where NIR represents the near-infrared band (Landsat TM: Band 4; OLI/OLI-2: Band 5), and SWIR represents the shortwave infrared band (Landsat TM: Band 5; OLI/OLI-2: Band 6).

The NDMI used in this study ranges from -1 to +1, with higher values consistently indicating dense, closed-canopy vegetation. To maintain programmatic consistency across the 35-year monitoring timeline, a pixel-based fixed threshold of $NDMI > 0.7$ was established to classify forest cover, adapting widely accepted empirical baselines for tropical canopy mapping (Choi et al., 2021; Piragnolo et al., 2021). This index was deliberately selected over traditional greenness indices like NDVI because NDMI effectively mitigates spectral saturation issues in dense tropical rainforests and is highly sensitive to canopy logging and perforations, where surface moisture drops rapidly upon tree extraction.

To mitigate the inherent methodological risks of sensor drift and inter-generational variance across multiple Landsat instruments (TM, OLI, and OLI-2), strict pre-processing protocols were enforced. Radiometric normalization and atmospheric comparability were systematically addressed using USGS Landsat Level-2, Collection 2, Tier 1 Surface Reflectance datasets. These products are analysis-ready and have been

cross-calibrated using the LEDAPS (TM) and LaSRC (OLI/OLI-2) (Wulder et al., 2022) atmospheric correction algorithms to ensure surface reflectance stability. Furthermore, temporal harmonization was maintained by targeting cloud-free composites within identical seasonal windows to avoid phenological bias. Lastly, the robustness and sensitivity of the >0.7 threshold were empirically validated through a rigorous chronological accuracy test. This is intended to ensure that the calibrated threshold yields highly reliable, low-bias historical forest area estimates throughout the observation period.

The model's temporal reliability in tracking historical forest cover changes was evaluated using a chronological transition matrix. Instead of validating static land-cover types, this matrix cross-compares the predicted forest-cover year with the observed historical reference years from 1990 to 2025 (Li et al., 2024). The chronological transition matrix is constructed by placing reference classes in rows and classification results in columns. Diagonal values in the matrix indicate the number of correctly classified pixels, while off-diagonal values indicate misclassification. Overall accuracy was calculated by dividing the number of correctly classified pixels by the total number of samples. In addition, producers' and users' accuracies were calculated for each year's class (Rawat et al., 2026). To measure the level of agreement corrected for random chance, the Kappa coefficient (Cohen's Kappa) was used. A Kappa value >0.80 is generally interpreted as very strong agreement, while 0.61 – 0.80 is categorized as strong agreement (Oo et al., 2026).

To mathematically robustify the historical evaluation, a total of 240 independent validation points were generated across the study area utilizing a stratified random sampling design. The samples were distributed equally to ensure strict chronological balance, with exactly 30

reference points allocated per target observation year. The spatial distribution of these validation points covered the entire study area to eliminate spatial clustering bias.

The ground-truthing verification was performed via high-resolution visual interpretation on Google Earth Pro and historical Landsat composite rollbacks. The temporal matching procedure paired each model output year with reference imagery windows targeted within a ± 6 -month tolerance of the specific target year. For earlier historical epochs (1990–1995) where sub-meter high-resolution imagery was limited, multi-spectral false-color composites from standalone Landsat archives were utilized as the primary chronological baselines. To maintain strict interpreter consistency, all 240 points were cross-examined using a double-blind consensus interpretation protocol by two independent GIS specialists, who assessed canopy shadow and texture patterns, thereby establishing an inter-rater agreement framework before the final accuracy calculation.

Next, the forest cover model was overlaid with land cover type maps and forest area function maps. Overlay analysis was conducted to identify the spatial distribution of forests across land-use categories and area functions. This approach allows for thematic spatial analysis to understand forest change patterns in the context of spatial planning and forestry policy. To enhance external validity, the forest cover model results were compared with Global Forest Watch (GFW) data, based on the Hansen et al. (2013) dataset on global tree cover change. The GFW dataset provides information on annual tree cover loss at 30 m resolution generated from global Landsat imagery. Comparisons were made by evaluating the correspondence between spatial patterns of forest loss and annual area trends between the research model results and GFW data.

The analysis was conducted by identifying a spatial pattern match. The differences that emerged were analyzed by considering differences in forest definitions, canopy cover thresholds, and classification methods used (Hansen et al., 2013).

Furthermore, the two models were structurally aligned by extracting their spatial extent. A spatial concordance analysis was performed using a confusion matrix to evaluate classification agreement between the local and GFW models at sample points. This process cross-classifies the study area into binary classes: forest and non-forest. The evaluation was conducted using 235 random sample points generated through a stratified random sampling approach. The number of points for each class was adjusted in proportion to each class's percentage of the area.

Four accuracy metrics are calculated from the contingency matrix: Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and Cohen's Kappa

Coefficient. OA Accuracy measures the percentage of sample points correctly classified into both classes (forest and non-forest) across the study area. This formula is calculated using Equation 2 as follows (Foody, 2024):

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

where TP, TN, FN, and FP represent True Positives, True Negatives, False Negatives, and False Positives, respectively.

PA Accuracy is used to calculate the proportion of actual forest sample points (based on the GFW reference) that the local model successfully detects. UA Accuracy measures the proportion of points classified as forest by the local model that are forest in the GFW data. Cohen's Kappa Coefficient is used as a more stringent index to evaluate classification agreement between the two models, accounting for chance. The overall workflow of the methodology is presented in Figure 2.

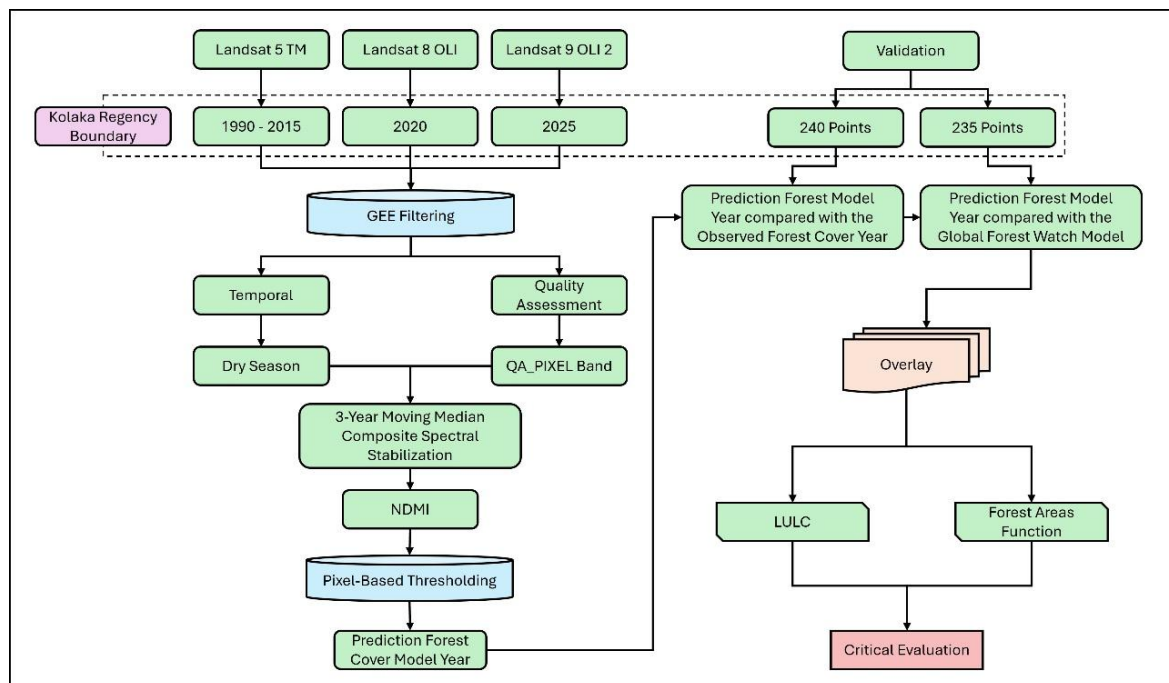


Figure 2. Workflow of the methodology.

Results

Forest cover change

The forest cover change model in Kolaka Regency shows fluctuations throughout the observation period. Forest cover in this

region from 1990 to 2005 continued to decline, with the largest decline occurring from 2000 to 2005, reaching 404,00 km². In the following year, forest cover increased to 319,20 km². However, a nearly identical decline occurred in the following period, reaching 303,18 km². In the following period, forest cover recovered, but only to

one-third of the loss. Compared to the baseline period, forest cover in Kolaka Regency had disappeared by 462,31 km² (Figure 3). This change demonstrates a dynamic pattern and requires special attention, particularly regarding forest management in this region.

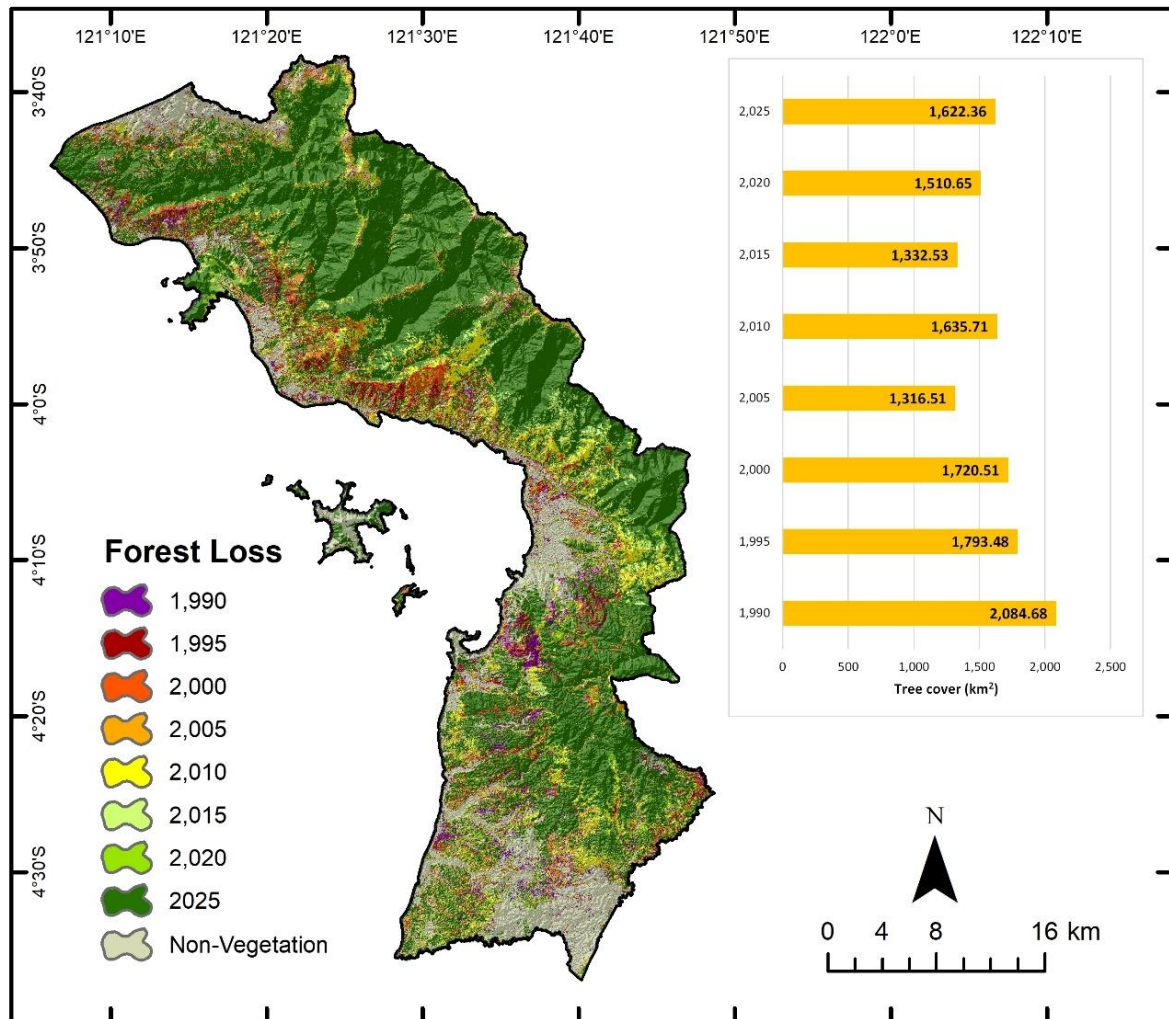


Figure 3. Forest Cover Changes in Kolaka Regency.

Overall, forest cover change in Kolaka Regency indicates an increase in deforestation intensity. Despite efforts to tighten forest governance policies and law enforcement over time, the reality on the ground demonstrates significant challenges in maintaining the region's sustainability. This aligns with the findings of Gunawan et al. (2024), who highlighted that overlapping industrial concessions and protected areas often trigger natural forest

loss, resulting in reduced biodiversity and ecosystem function degradation. This study indirectly emphasizes the importance of integrating spatial-temporal data into evidence-based conservation planning to monitor the effectiveness of forest protection policies in affected area.

Accuracy Test

Accuracy testing of forest cover maps from 1990 to 2025 in Kolaka Regency

demonstrated high data reliability. The accuracy test using a confusion matrix yielded an OA value of 80.41% with a Kappa coefficient of 0.77. This value indicates that the forest cover classification generated by the GEE thresholding algorithm exhibits high consistency and is suitable for long-term land-use change analysis.

Specifically, UA accuracy demonstrated impressive performance in the 2025 (100%) and 2020 (93.34%) classifications. This demonstrates that the Landsat 8 OLI

and 9 OLI-2 sensors can distinguish forest objects with greater precision than previous-generation sensors. However, PA accuracy varied during the intermediate period (Table 2), particularly in 2005 (68.57%) and 2010 (68.42%). The decrease in accuracy during this period was most likely caused by persistent atmospheric disturbances (cloud cover) in the Mekongga mountain region, as well as the similarity of spectral values between degraded secondary forests and cocoa or clove plantations that began to expand in Kolaka during this period.

Table 2. Forest cover model accuracy test.

Year		Observed forest cover year								Total	UA
		1990	1995	2000	2005	2010	2015	2020	2025		
Predicted forest cover year	1990	21	-	-	-	4	-	-	5	30	70
	1995	-	19	-	-	7	2	-	2	30	63.34
	2000	-	-	27	2	-	-	-	1	30	90
	2005	-	-	1	24	1	-	2	2	30	80
	2010	-	-	-	4	26	-	-	-	30	86.67
	2015	-	-	3	5	-	18	2	2	30	60
	2020	-	-	-	-	-	1	28	1	30	93.34
	2025	-	-	-	-	-	-	-	30	30	100
Total		21	19	31	35	38	21	32	43	240	
PA		100	100	87.09	68.57	68.42	85.71	87.50	69.77		
OA = 80.41						Kappa = 0.77					

Comparative Analysis of Models Against Global Forest Watch

A spatial comparison was conducted between the developed GEE-based vegetation index model and the Global Forest Watch reference data to validate tree-cover loss patterns. Visually, the developed model demonstrated greater accuracy in capturing local-level land-cover dynamics than the GFW data did.

The research model (Figure 4a) identified forest fragmentation and tree loss patterns in hilly areas in greater detail. In contrast, the GFW data (Figure 4b) tended to generalize to areas of vegetation transition. The detected tree loss patterns (marked in orange) showed high location consistency between the two models, particularly in coastal and foothill areas, which are active zones of land conversion. The use of a

custom vegetation index in the GEE script enabled more sensitive detection of canopy change in areas with steep topography in Kolaka Regency, where GFW data often suffers from noise due to slope-shadow distortion.

To provide a rigorous validation, a point-based spatial intercomparison analysis was conducted between the two models (Figure 5). The contingency matrix analysis demonstrated an OA of 85.11% across the study area. Focusing on the forest class, the model achieved a PA of 77.42% and a UA of 69.57%. Furthermore, the Cohen's Kappa coefficient was 0.63, indicating a substantial spatial agreement between the local model and the GFW baseline. This strong alignment confirms that the local model successfully captures the distribution of primary forests while maintaining high predictive reliability.

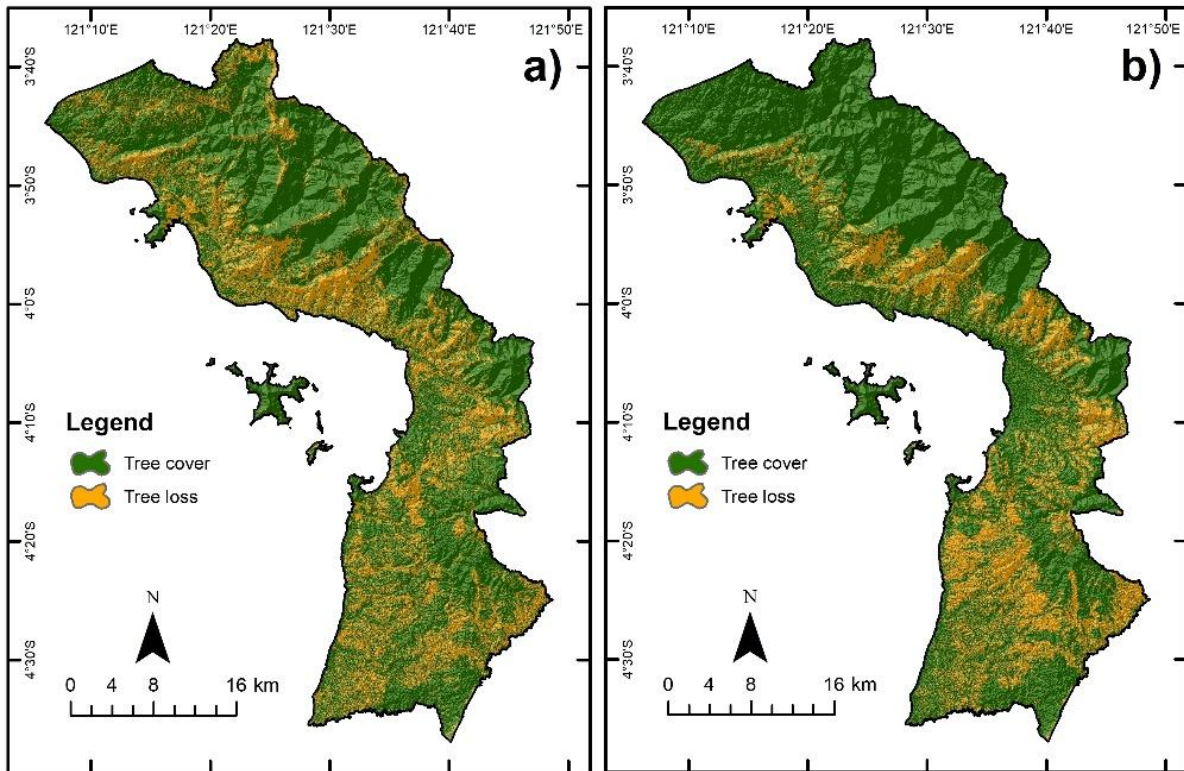


Figure 4. Model comparison between a) the GEE-based forest cover model, and b) the Global Forest Watch model.

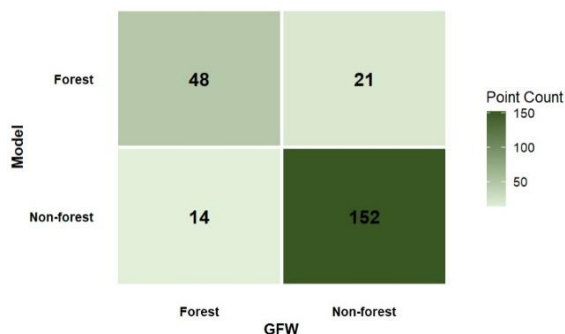


Figure 5. Point-based confusion matrix demonstrating the classification agreement between the vegetation index model and the Global Forest Watch model

Spatial cross-tabulation of forest cover models on land cover and forest area function

To provide rigorous validation and to understand the underlying spatial drivers of forest dynamics, a spatial cross-tabulation matrix analysis was conducted by intersecting the forest model with regional Land Use and Land Cover (LULC) classes (Figure 6) and official Forest Area Functions (Figure 7). This transition framework shifts the interpretation from a

purely visual comparison to a robust, analytical evaluation of spatial alignment and localized discrepancies.

The intercomparison with the LULC baseline (Figure 6) demonstrates that, of the 2,638.57 km² total reference forest area, the local model confirms a high spatial persistence of 1,876.03 km² as stable tree cover. However, a critical structural divergence is uncovered, revealing 762.54 km² of tree loss within the designated forest baseline. This substantial discrepancy represents fragmented canopy degradation or secondary forest regrowth that global-scale datasets typically generalize or omit.

Anthropogenic pressures along forest boundaries are quantified, with the model capturing tree-cover extensions into non-forest classes, including built-up areas (47.59 km²) and crops (29.11 km²). Conversely, the detection of tree loss overlapping with bare ground (10.64 km²), built-up clusters (23.14 km²), and shrublands (26.74 km²) provides empirical evidence of persistent land clearing and

infrastructure expansion encroaching upon the core forest matrices.

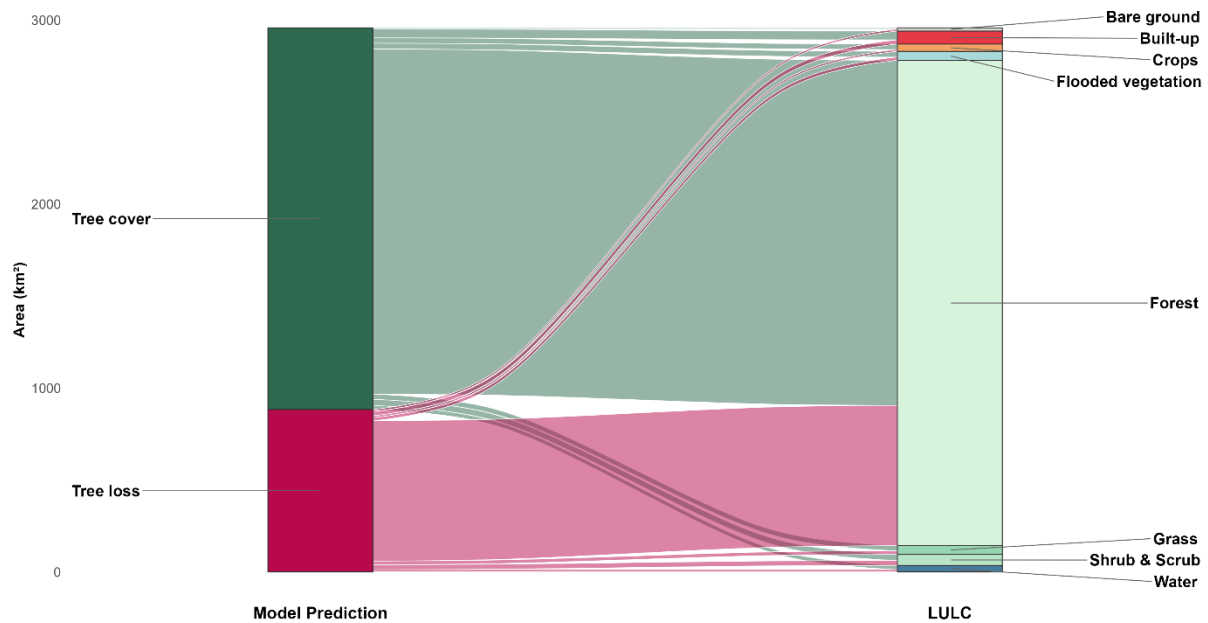


Figure 6. Transition of the local forest cover model illustrating quantitative alignment against baseline LULC.

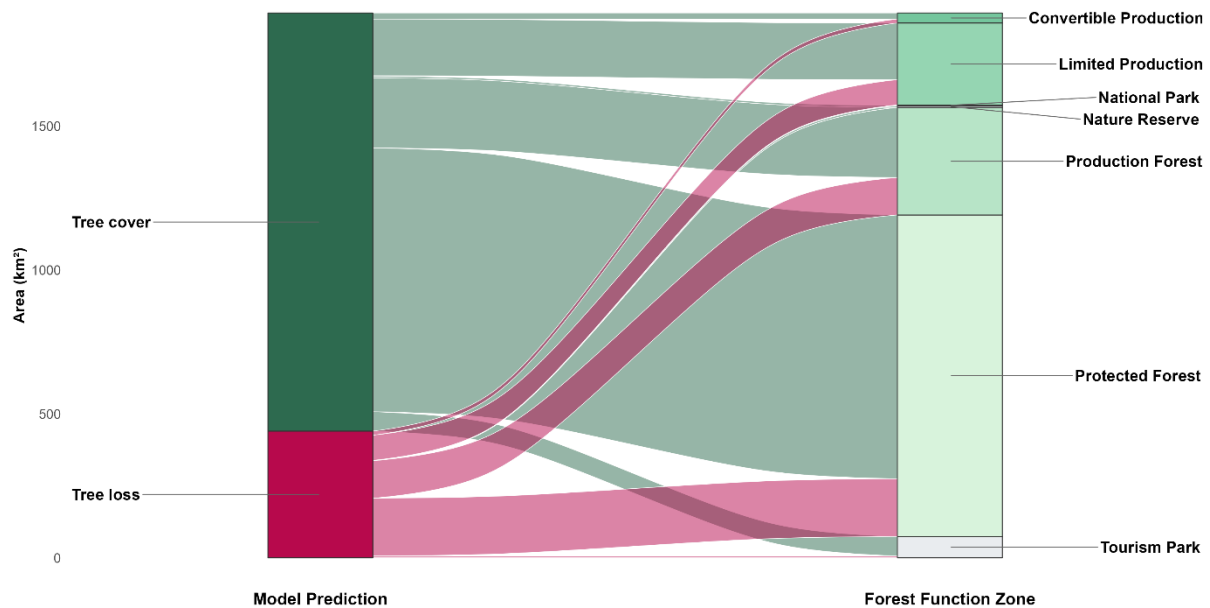


Figure 7. Transition of the local forest cover model illustrating spatial distribution of stable tree cover and localized tree loss across forest function zones

When evaluated against administrative boundaries (Figure 7), the spatial transition reveals critical insights into compliance and management. A total of 916.37 km² of stable tree cover is localized within Protected Forests, validating the ecological persistence of the region's core conservation zones. Nevertheless, the overlay successfully identifies a severe

environmental hotspot: a total of 200.77 km² of tree loss has occurred within these legally protected domains, representing approximately 18% of the protected baseline and placing it under critical threat.

Furthermore, forest extraction dynamics are heavily concentrated within commercial zones, where Production Forests and

Limited Production Forests account for a combined tree loss of 217.79 km² (130.08 km² and 87.71 km², respectively). Because production-related allocations (Production, Limited Production, and Convertible Production Forests) collectively account for over 50% of the managed landscape, the study area exhibits extreme systemic vulnerability to legal canopy modifications through timber utilization permits. The tight spatial overlap between tree loss and bare ground within these production blocks confirms that localized extractive activities, such as mining and agroforestry conversions, are the primary structural drivers creating deforested perforations within the legal forest estate.

Discussion

The long-term multi-decadal forest loss captured in Kolaka Regency indicates a massive landscape transformation. The drastic decline witnessed during the 2000–2005 epoch directly reflects the institutional impacts of the post-decentralization exploitation boom, where the devolution of natural resource management authority often preceded the readiness of regional oversight instruments. The subsequent vegetation recovery phase, which compensated for only one-third of the total historical loss, underscores the low resilience of these dense tropical ecosystems to large-scale, compounded anthropogenic disturbances.

The inability of forests to return to their original state signals an irreversible loss of ecosystem services. This aligns with the findings of Gaveau et al. (2021), which demonstrate that primary forest degradation in Indonesia remains largely permanent, as these areas are immediately converted into industrial plantations or mining sites. Such conversions, particularly in mining sectors, result in irreversible ecological shifts that prevent natural forest regeneration (Giljum et al., 2022). A comparison with the study by Hansen et al. (2013) shows that Sulawesi is characterized by more fragmented

deforestation than Kalimantan. This fragmentation increases the risk of extinction for endemic species by reducing habitat connectivity in the Wallacea region (Supriatna et al., 2020). This study indirectly emphasizes the integration of spatial-temporal data in evidence-based forest conservation planning.

An OA value of 80.41% and a Kappa of 0.77 provide scientific evidence that the GEE thresholding algorithm is highly effective for long-term monitoring in complex topographic areas. However, the low PA observed during the 2005–2010 period highlighted the challenge of spectral mixing between degraded secondary forests and agroforestry plantations (cocoa/cloves). In Kolaka, the expansion of smallholder agriculture often mimics the forest spectral profile in medium-resolution satellite imagery, leading to omission errors. This finding aligns with Escobar-López et al. (2024), who noted that overlapping industrial concessions and complex smallholder landscapes typically complicate automated object discrimination when relying solely on generic passive remote sensing frameworks.

When overlaid with administrative boundaries, the overlay reveals that more than 50% of the study area falls within production-related zones (Limited Production Forest, Production Forest, and Convertible Production Forest), thereby placing the forest ecosystem of Kolaka at high risk of legal canopy modifications (Figure 7). Furthermore, the explicit detection of localized bare-ground perforations clustered within these designated production boundaries structurally signifies the extensive spatial footprint of extractive activities.

While a definitive causal link to corporate boundaries requires decoupled tenure datasets, these bare-ground signatures can be critically contextualized within the

regional footprint of the extractive boom. Historically, the intensity of land clearing in Kolaka exhibits a strong socio-economic alignment with global nickel market dynamics. As a strategic landscape containing one of the largest saprolite ore reserves in the region, local forest extraction trends tend to fluctuate in tandem with the escalating demand for nickel within the global electric vehicle battery supply chain. This structural linkage illustrates a critical, localized green economy paradox, in which global-scale decarbonization efforts are fundamentally offset by severe, irreversible deforestation at the resource frontier.

This contextual trajectory is well supported by Giljum et al. (2022), who argued that industrial mining is the most permanent and destructive driver of forest loss compared with transitional shifts in the agricultural sector. The extractive nature of nickel mining, particularly across the ultrabasic structures of Sulawesi, causes profound disruptions to soil profiles and structural damage, rendering subsequent ecosystem recovery highly protracted and ecologically difficult (D'Alisa & Demaria, 2024). Furthermore, macro-scale observations by Lo et al. (2024) across Indonesia's nickel belt confirm that mining expansion drives systemic fragmentation of forest cover through both direct surface stripping and the cumulative development of supporting transport infrastructure.

The biophysical ramifications of this extractive pressure extend beyond commercial production blocks; they severely compromise core conservation zones. The stark spatial disparity captured between the official legal status of Protected Forests and the high rates of actual canopy loss empirically indicates that an administrative designation does not automatically guarantee vegetation persistence on the ground. Beyond complete canopy removal, the model's successful isolation of extensive

transitional Shrub & Scrub areas reflects a substantial accumulation of degraded, idle post-extraction land parcels that have systematically failed to undergo active environmental rehabilitation.

Consequently, these ecological indicators demand an urgent paradigm shift. Forest management in Kolaka must decisively migrate from an archaic, purely administrative compliance approach to a dynamic, real-time spatial monitoring framework. Without stringent law enforcement mechanisms that actively integrate GEE-automated monitoring, the region's remaining core forest cover will continue to be chronically eroded under the guise of expanding forest area through borrow-to-use permits.

Ultimately, this study underscores that high-resolution spatio-temporal data integration must serve as the primary instrument in evidence-based conservation planning. Deploying such localized automated systems is no longer optional, but a vital ecological necessity to prevent the imminent collapse of the hydrological buffering capacity across the critical Mangolo watershed and its surrounding upstream catchments. To bridge the empirical boundaries of this current study with these broader institutional drivers, future investigations must integrate temporal mineral production statistics, commodity pricing models, and spatial mining concession maps into this biophysical remote sensing framework to quantitatively map the direct socio-economic causalities of long-term forest loss.

While the GEE-based localized thresholding framework demonstrated a high operational capacity, several inherent remote sensing constraints must be acknowledged as potential sources of uncertainty propagation within this tropical landscape. First, the 30-meter spatial resolution of the Landsat instruments

naturally introduces the challenge of mixed pixels along highly fragmented forest edges and agroforestry transitions, where sub-pixel combinations of tree canopy, smallholder crops, and bare soil may artificially distort the uniform >0.7 index boundary. Second, despite enforcing strict bitwise logical masking protocols using the QA_PIXEL band, persistent tropical cloud contamination and localized atmospheric haze residuals remain an inevitable source of minor spectral noise across historical annual mosaics (Singh et al., 2025).

Furthermore, the highly complex, rugged topography of the Mekongga Mountains introduces severe shadowing in mountainous terrain. These topographically shaded slopes inherently exhibit reduced surface reflectance, which can lead to local underestimation of canopy density if the spectral index relies solely on visible greenness (Jiang et al., 2019). Lastly, vegetation spectral overlap poses a distinct conceptual challenge in this region; mature commercial agroforestry matrices (such as dense cacao or clove plantations) frequently exhibit near-identical multi-spectral canopy signatures to those of primary or secondary tropical forest estates (Ordway et al., 2017; Pain et al., 2021).

Nevertheless, the propagation of these spectral and spatial uncertainties was successfully constrained and substantially mitigated by our implementation of the 3-year moving-median composite window and strict dry-season temporal filtering, which effectively suppressed ephemeral noise and terrain illumination variability. Empirically, the robustness of the framework is verified by the chronological accuracy assessment (Table 2), where the model maintained high stability. This demonstrates that, despite these structural challenges, the calibrated fixed-threshold approach yields a reliable and chronologically consistent trajectory of long-term forest-cover dynamics.

Conclusion

This study concluded that forest cover in Kolaka Regency experienced significant fluctuations with a progressive degradation trend, with cumulative forest loss reaching 462,31 km² since the baseline period. The sharpest decline occurred in the 2000–2005 period, reaching 404,00 km². Despite a phase of vegetation recovery, the recovered area only replaced one-third of the total forest loss, indicating a permanent decline in ecosystem function and biodiversity.

Methodologically, the classification model using the thresholding algorithm on the GEE platform proved highly reliable, with an OA value of 80.41% and a Kappa coefficient of 0.77. The use of Landsat 8 and 9 sensors achieved 100% user accuracy by 2024, demonstrating the superiority of this local model in capturing the spatial details of tree loss in steep topographic areas compared to global reference data, while successfully constraining inherent uncertainties such as mixed pixels, cloud residuals, terrain shadowing, and spectral overlap.

Overlay analysis confirms that the primary drivers of deforestation in Kolaka are extractive mining and land conversion, particularly in Production Forest areas, which account for more than 50% of the study area. The presence of bare ground and scrubland within production forest areas underscores their vulnerability to legal deforestation, as evidenced by a substantial accumulation of unrehabilitated, idle post-mining land. Therefore, integrated real-time monitoring and zoning evaluation are needed to protect the remaining 45.61% of the Protected Forest from mining pressures. To fully solidify this framework, future investigations must integrate corporate concession boundaries and temporal production statistics into this biophysical remote sensing model.

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Author Contribution

Septianto Aldiansyah designed the research method, data analysis, and interpretation of results, drafted the publication manuscript; Amniar Ati conducted data analysis and interpretation of results; and Fitriyani Saudi refined the issues and reviewed the publication manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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