Urbanisation driven spectral–structural divergence in forest extent: threshold-based validation using GEDI LiDAR in Ekiti State, Nigeria

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Abstract:

Forest degradation in rapidly urbanising tropical regions is often underestimated due to reliance on two-dimensional spectral indicators that inadequately capture vertical forest structure. This study evaluates the reliability of satellite-derived forest extent in Ekiti State, Nigeria, by integrating multi-sensor remote sensing data with spaceborne LiDAR from the Global Ecosystem Dynamics Investigation.

Land use/land cover (LULC) dynamics between 2007 and 2024 were mapped using a fusion of Synthetic Aperture Radar (Sentinel-1 and ALOS PALSAR) and optical datasets (Landsat and Sentinel-2). Results indicate a decline in forest cover of 540.10 km^2 (−25.34%) alongside a 266.42% increase in built-up area, corresponding to an Urban Land Consumption Ratio (ULCR) of 3.12, reflecting spatially inefficient urban expansion and increasing anthropogenic pressure on forest landscapes.

To assess classification reliability, LULC-derived forest extent was validated against GEDI-derived canopy height using two structural thresholds (≥5 m and ≥10 m). At the 5 m threshold, agreement was consistently low (F1 = 0.581 in 2020; 0.497 in 2025), driven by very low recall (<0.41), indicating substantial omission of structurally defined forest. In contrast, the 10 m threshold yielded higher agreement (F1 = 0.745 in 2020; 0.662 in 2025), suggesting improved alignment with spectrally derived forest extent. However, a consistent decline in F1-score across both thresholds demonstrates increasing divergence between spectral classification and structural forest definition over time.

A moderate reduction in mean canopy height (10.6 m in 2020 to 9.34 m in 2025) further indicates ongoing structural degradation. Analysis of anthropogenic drivers reveals that urbanisation intensity, rather than population growth, is the dominant driver of both vegetation decline and structural change. These findings provide empirical evidence of threshold-dependent and temporally evolving spectral–structural decoupling, highlighting the need to integrate LiDAR-derived structural metrics into forest monitoring frameworks.

Keywords: Multi-sensor fusion, GEDI LiDAR, Deforestation monitoring, Urban Land Consumption Ratio (ULCR), Canopy height model (CHM).

Introduction

Forest degradation in tropical regions is increasingly driven by the combined pressures of deforestation and rapid urbanisation, particularly in sub-Saharan Africa where urban expansion is projected to intensify in the coming decades (UN DESA, 2019; Seto et al., 2012). In Nigeria, these dynamics are especially pronounced, with widespread conversion of forested landscapes into agricultural and built-up areas, resulting in substantial losses in ecosystem integrity, biodiversity, and carbon storage (Fasona et al., 2016). In Ekiti State, land use/land cover (LULC) analysis has documented a 51.25% decline in forest cover between 1972 and 2017, largely driven by agricultural expansion and urban growth (Olorunfemi et al., 2018), highlighting a long-term trajectory of anthropogenic landscape transformation.

Remote sensing has become the primary tool for monitoring forest dynamics at regional and global scales. Optical satellite data, particularly Landsat and Sentinel-2, have been widely used to assess vegetation condition through spectral indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), enabling consistent mapping of deforestation and vegetation change (Hansen et al., 2013). In parallel, Synthetic Aperture Radar (SAR) data (e.g., Sentinel-1 and ALOS PALSAR) provide all-weather capability and sensitivity to vegetation structure, improving monitoring in cloud-prone tropical environments (Hirschmugl et al., 2024). The integration of optical and SAR data has further enhanced the detection of land-use change and urban expansion in heterogeneous landscapes (Mullissa et al., 2024).

Despite these advances, conventional forest monitoring remains largely dependent on two-dimensional spectral representations of vegetation. Spectral indices are primarily sensitive to canopy surface properties and tend to saturate in dense vegetation, limiting their ability to capture vertical forest structure such as canopy height, biomass, and structural complexity (Potapov et al., 2021). As a result, degraded forests, secondary regrowth, and shrub-dominated systems may retain high spectral greenness despite substantial reductions in ecological functionality. This limitation is particularly critical in rapidly urbanising tropical landscapes, where anthropogenic disturbances often alter vertical structure without immediately affecting spectral signatures.

This mismatch gives rise to spectral–structural decoupling, where horizontal vegetation signals derived from optical and SAR data diverge from the underlying three-dimensional condition of the ecosystem. Under such conditions, satellite-derived forest extent may systematically overestimate forest condition, masking structurally degraded or "cryptic" forest states. Although this issue is increasingly recognised, empirical validation of satellite-derived forest extent using three-dimensional structural data remains limited, particularly in tropical Africa.

Recent developments in spaceborne LiDAR, such as the Global Ecosystem Dynamics Investigation (GEDI), provide an opportunity to address this limitation by directly measuring vertical forest structure, including canopy height and vegetation profiles (Potapov et al., 2021; Fayad et al., 2021). Integrating GEDI with multi-sensor remote sensing enables a more comprehensive assessment of forest condition by linking horizontal extent with vertical structure. However, few studies have explicitly applied such integration to evaluate the reliability of satellite-derived forest extent in the context of rapid urbanisation.

This study aims to evaluate the reliability of satellite-derived forest extent in Ekiti State, Nigeria, by integrating multi-sensor remote sensing data with GEDI-derived canopy height. A threshold-based structural validation framework is applied to quantify agreement between spectral classification and structural forest definition across time. Specifically, the study introduces a canopy height threshold approach (≥5 m and ≥10 m) to assess spectral–structural divergence and its temporal evolution under increasing urbanisation pressure.

Study Area

Ekiti State in Figure 1 is located in southwestern Nigeria between latitudes 7°15′N–8°05′N and longitudes 4°45′E–5°45′E (Adegboyega and Adebayo, 2018). The state covers approximately 5,435 km² and is characterised by a tropical climate with mean annual rainfall of about 1,200 mm and temperatures ranging from 27–32°C. It lies within the rainforest–Guinea savanna transition zone, resulting in a heterogeneous vegetation structure comprising dense forest in the south and savanna vegetation in the north.

The state has experienced rapid population growth, increasing from approximately 2.38 million in 2006 to an estimated 3.69 million in 2023 (NBS, 2006), accompanied by significant expansion of built-up areas and agricultural land. This combination of ecological diversity and increasing anthropogenic pressure makes Ekiti State a suitable case study for assessing urbanisation-driven forest degradation and structural change.

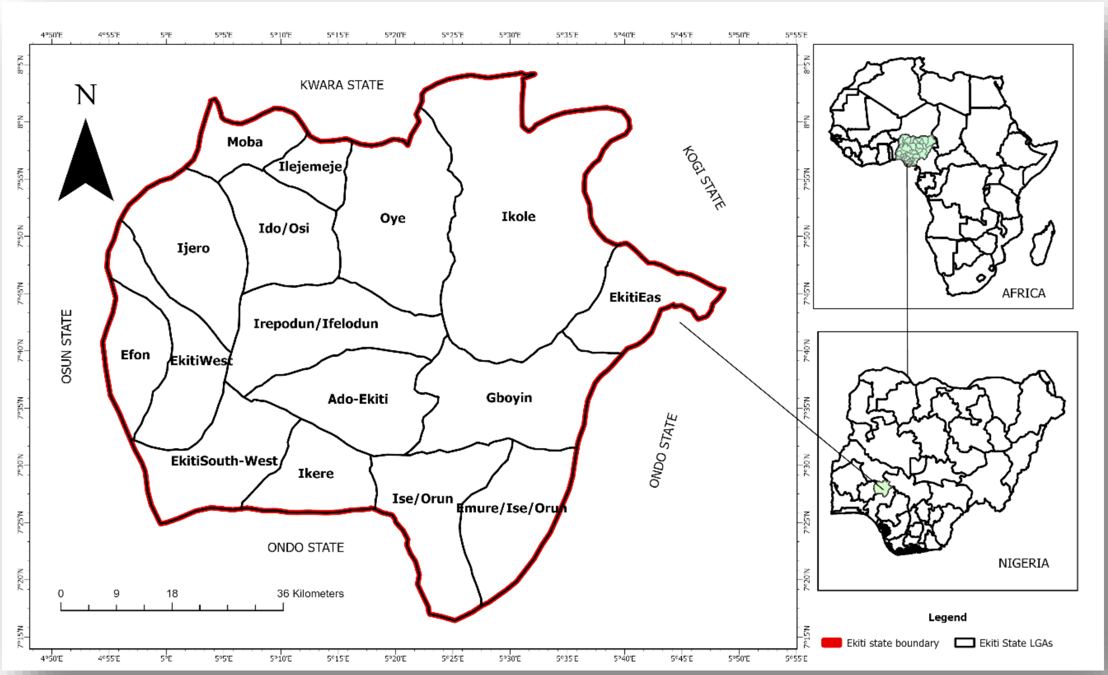

Figure 1: Ekiti State, Nigeria

Source: Author, 2026.

Methodology

This study utilised both primary and secondary datasets. Primary data included multi-sensor satellite imagery (Landsat, Sentinel-1, Sentinel-2, and ALOS PALSAR), while secondary data included population statistics obtained from the National Population Commission. The datasets used and their respective roles are summarised in Table 1.

For canopy height modelling, a multi-sensor set of predictor variables was constructed from optical, SAR, and terrain data sources. These predictors are detailed in Table 2.

Table 1: Data and Sources

Data	Sources	Resolution	Role
L-Band (ALOS-2 PALSAR-2)	JAXA	25m	Physical structure & biomass
Landsat 7 ETM+ and Landsat 8	NASA/USGS	30m	LULC, NDBI
Sentinel-1 (C-band)	ESA (Copernicus)	10m	Surface roughness and upscaling GEDI height metrics
Optical & Red-Edge (Sentinel-2)	ESA (Copernicus)	10m	Vegetation health, red-edge indices for canopy differentiation
SRTM (30m)	NASA	30m	Elevation & Slope

WorldCover (10m)	ESA (Copernicus)	10m	Reference purpose
GEDI L2A/L2B	NASA LP DAAC	25m	Vertical canopy profile and RH (98) height calibration
Population	National Population Commission		Population Growth

Table 2: Predictors

Category	Variable(s)	Source	Functional role in modelling
Optical (Sentinel-2)	B2, B3, B4, B8, B11, B12	Sentinel-2	Spectral reflectance; vegetation and moisture sensitivity
Vegetation Indices	NDVI, NDMI, NBR	Derived from S2	Canopy greenness, moisture, disturbance detection
SAR backscatter	VV, VH (Sentinel-1); HH/HV (PALSAR)	Sentinel-1, PALSAR	Structural information, canopy penetration
SAR Derived Metrics	Backscatter ratios (VV/VH, HH/HV, RVI, GLCM texture metrics)	Sentinel-1 PALSAR	Canopy density, and structural complexity
Terrain	Elevation, Slope, TWI	SRTM DEM	Topographic controls vegetation distribution

Deforestation rate in Ekiti State

Land use/land cover (LULC) classification for Ekiti State was conducted using a multi-sensor data fusion approach in Google Earth Engine (GEE). To address cloud contamination and Landsat 7 SLC-off gaps in 2007, optical imagery (Landsat 7 ETM+) was combined with L-band SAR data from ALOS PALSAR. SAR data were filtered using a focal median filter (2-pixel radius), while Landsat imagery was processed as a multi-date median composite and cloud-masked using the QA_PIXEL band.

A predictor stack comprising spectral bands (Landsat), SAR backscatter (HH, HV), Radar Vegetation Index (RVI), and terrain (SRTM-derived slope) was constructed to improve class separability. Classification was performed using Random Forest (RF) and Support Vector Machine (SVM) algorithms. Training samples for six classes (Water, Barren, Built-up, Agriculture, Shrubland, and Forest) were manually digitised and split into 70% training and

30% validation datasets. Model performance was assessed using confusion matrix metrics, including overall accuracy and Kappa coefficient.

Deforestation rates were quantified based on changes in forest area across three epochs (2007, 2014, and 2024). To evaluate structural forest integrity, the LULC-derived forest extent was compared with GEDI-derived canopy height data. A 5 m height threshold, consistent with FAO forest definition, was applied to delineate structurally valid forest. This enabled the identification of areas where spectral classification overestimates forest condition despite reduced vertical structure.

Urbanisation Trends in Ekiti State

Urbanisation metrics

Urbanisation was analysed using the population, built-up areas and Urban land consumption (Ewing et al. 2002 and Güneralp et al. 2017) calculated using equation 1.

Urban Land Consumption Ratio (ULCR)

$$ULCR = \frac{\frac{Bu_t}{Bu_{t-1}}}{\frac{P_t}{Pt_{-1}}} \qquad (1)$$

Where, Bu_t = Built up area in time (t), Bu_{t-1} =Built up area in time (t-1), Pt (Population in time t), P_{t-1} (population in time t-1). Which is the ratio of the land consumption rate to the population growth rate.

Characterisation of forest structure

GEDI Level 2A data were downloaded using the Python API (EarthAccess) in Google Colab and imported into Google Earth Engine (GEE). Multi-sensor predictor variables (Sentinel-2, Sentinel-1, and ALOS PALSAR) were extracted at GEDI footprint locations using the sampleRegions function.

A total of 18,000 randomly sampled points were used for canopy height modelling, with GEDI RH98 as the target variable. This sample size was standardised across both 2020 and 2025 to ensure comparability, as the number of available GEDI observations differed between the two periods. Random sampling ensured spatial representation across the study area while minimising bias associated with unequal sample sizes.

Model development and validation were conducted in Google Colab using Random Forest (RF) and Extreme Gradient Boosting (XGBoost) algorithms, with data split into training and testing subsets. Model performance was evaluated using standard regression metrics (R^2, RMSE, and MAE).

The trained models were applied in GEE to generate wall-to-wall canopy height maps at 25 m spatial resolution. An NDVI threshold (NDVI > 0.12) was applied to remove non-vegetated areas, and a final mask derived from the LULC classification was used to exclude water bodies.

To maintain temporal consistency, ALOS PALSAR-1 (2007–2010) and PALSAR-2 (2014–2024) datasets were used. Missing data for 2011–2014 were estimated using an empirical relationship between Radar Vegetation Index (RVI) and NDVI. The Radar Vegetation Index (RVI) was computed in equation 2:

$$RVI = \frac{4\,VH}{VH+HH} \tag{2}$$

The effect of urbanisation (NDBI) and Demography (Population) on vegetation health and forest structure.

The relationships between urbanisation metrics—Normalized Difference Built-up Index (NDBI) and population—and ecological indicators, including vegetation health (NDVI) and structural condition (Radar Vegetation Index, RVI), were analysed for the period 2007–2024.

Kendall's Tau correlation was applied due to the non-normal distribution of the time-series data. In addition, Multiple Linear Regression (MLR) was used to assess the influence of urbanisation variables (population and NDBI) on vegetation health (NDVI) and forest structural condition (RVI).

NDBI and NDVI were derived in Google Earth Engine (GEE) using the following expressions: The NDBI and NDVI were derived using Google Earth Engine (GEE) based on Equations 3 and 4

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \tag{3}$$

$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{4}$$

Where: SWIR is the Short-Wave Infrared band, NIR is Near-Infrared band, and RED is the red band.

Threshold-based structural validation and spectral–structural divergence

Canopy height data from the Global Ecosystem Dynamics Investigation were used to define structural forest extent. CHM layers were converted to binary forest/non-forest masks using two thresholds (≥5 m and ≥10 m), representing minimum and stricter structural criteria, respectively. LULC maps for 2020 and 2025 were similarly reclassified into binary classes (forest = 1; non-forest = 0). All datasets were aligned to a common resolution, projection, and extent prior to analysis.

A pixel-wise overlay between LULC and CHM masks was performed to derive true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). From these, precision, recall, F1-score, and overall accuracy were computed to quantify agreement between spectral and structural forest definitions.

Spectral–structural divergence was assessed by comparing these metrics across thresholds and time periods. Variations in F1-score and recall were used to evaluate sensitivity to canopy height definition and temporal changes in agreement.

Results

Model Performance:

The Random Forest model demonstrated moderate predictive performance for canopy height estimation in both study years, with R^2 values of 0.35 for 2020 and 0.43 for 2025 (Table 3). The model achieved RMSE values of 4.38 m and 4.26 m, and MAE values of 3.39 m and 3.32 m for 2020 and 2025, respectively. A slight improvement in model performance was observed in 2025, reflected in the higher R^2 and lower error metrics compared to 2020.

Table 3: Random Forest model performance for canopy height prediction (2020–2025)

Year	**Model**	**R^2**	**RMSE (m)**	**MAE (m)**
2020	Random Forest	0.35	4.38	3.39
2025	Random Forest	0.43	4.26	3.32

Deforestation rate in Ekiti State

Figure 2 presents the spatial distribution of Land Use/Land Cover (LULC) classes in Ekiti State for 2007, 2014, and 2024. The classified maps depict six major land cover categories: water bodies, rock outcrops, built-up areas, agricultural lands, shrubland, and forest. These classes are represented using a consistent colour scheme: water (blue), rock outcrops (grey), built-up areas (red), agricultural land (orange), shrubland (yellow), and forest (green).

In 2007, classification using Landsat 7 imagery produced overall accuracies of 72.48% for Random Forest (RF) and 29.13% for Support Vector Machine (SVM). Class-wise accuracy for RF was highest for water (100%) and built-up areas (86.3%), followed by forest (67.3%) and rock outcrops (66.1%), while agriculture (58.2%) and shrubland (50.8%) recorded lower values.

By 2014, overall classification accuracies were 76.94% for SVM and 75.96% for RF. Class-level accuracies were highest for water (100%) and built-up areas (89.7%), while agriculture (61.7%) and shrubland (56.3%) recorded lower values.

In 2024, SVM achieved an overall accuracy of 85.3%, compared to 76.5% for RF. Class-level accuracies were highest for built-up areas (95.4%) and rock outcrops (92.6%), while agriculture (77.0%) and shrubland (71.2%) remained comparatively lower.

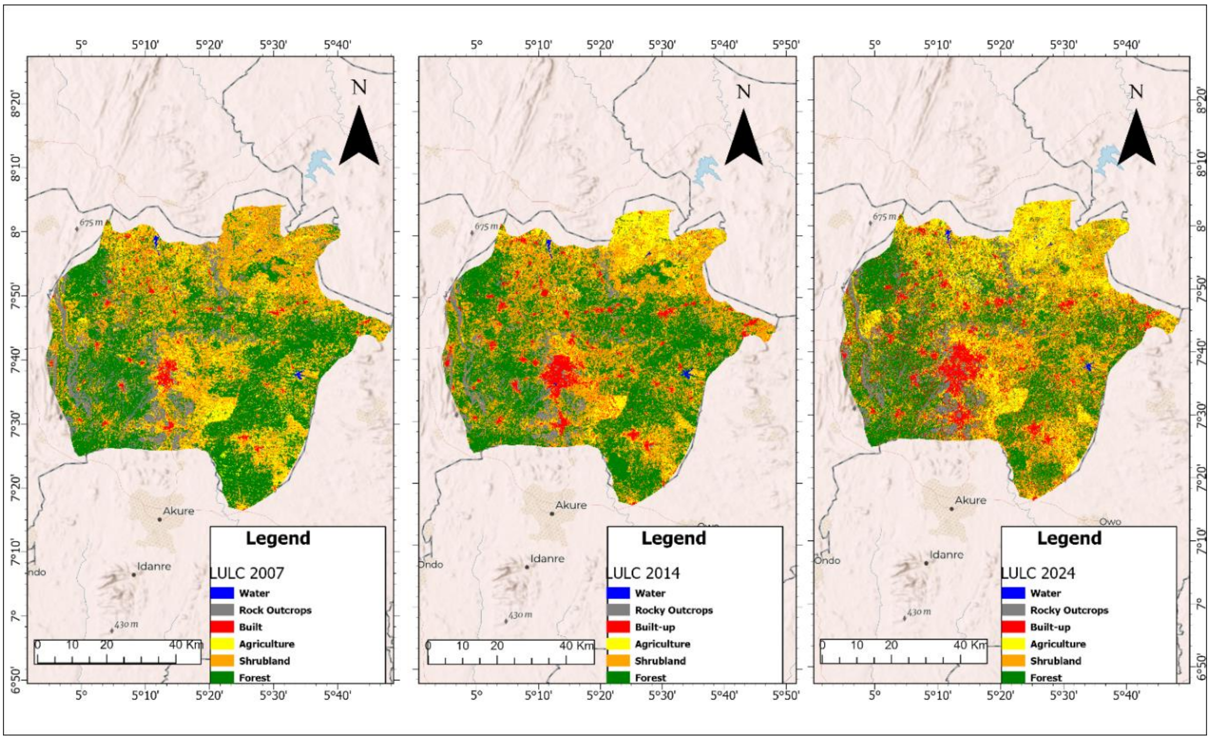

Figure 2: Land use land cover 2007 2014, and 2024.

The areal statistics (Table 2) present the distribution of LULC classes over the study period. In 2007, Ekiti State was predominantly covered by forest (2131.03 km²) and shrubland (1689.45 km²). Agricultural land covered 738.06 km², while built-up areas accounted for 158.23 km². Built-up areas were concentrated in major settlements such as Ado-Ekiti, Ikere, Ikole, Ido-Ekiti, Ora, Omuo, and Ilogbo.

By 2014, built-up areas increased to 330.66 km², representing an increase of 108.97% from 2007. Forest cover increased slightly by 8.53 km². Agricultural land decreased to 530.52 km², while rock outcrops reduced to 376.08 km².

In 2024, built-up areas increased further to 579.79 km², representing a 266.42% increase from 2007. Agricultural land expanded to 1016.51 km². Forest cover declined to 1590.93 km², corresponding to a loss of 540.10 km² (54,010 hectares). Shrubland decreased to 1610.95 km², representing a change of −4.64%.

Urbanisation in Ekiti State, Nigeria.

Urbanisation in Ekiti State between 2007 and 2024 in Figure 3 shows a clear and sustained upward trend, closely linked to population growth and the expansion of built-up areas. Over this period, the population increased from approximately 2.46 million in 2007 to about 3.74 million in 2024, representing a total growth of 51.72%. This growth follows a near-linear pattern, with an estimated average annual increase of about 76,670 people. Such steady demographic expansion has continuously intensified the demand for housing, infrastructure, and food production, thereby exerting pressure on available land resources.

Urbanisation in trend in Ekiti State

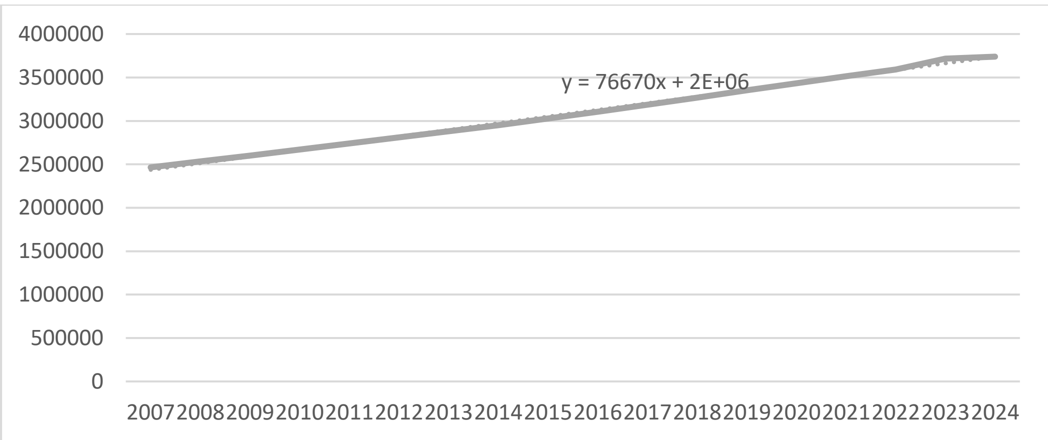

Figure 3: Change in population between 2007 to 2024

Source: Author, 2026

Between 2007 and 2024, the population of Ekiti State increased from 2,464,735 to 3,739,564, representing a growth of 51.72% as shown in Table 4. Over the same period, built-up area expanded from 158.23 km² to 579.79 km², corresponding to an increase of 266.42%. The Urban Land Consumption Ratio (ULCR) averaged 3.12, indicating that built-up expansion occurred at a rate more than three times that of population growth.

In parallel, forest area declined by approximately 540.10 km² (54,010 ha), while built-up areas increased by 421.56 km² over the same period

Table 4: Percentage change in population and built-up areas

YEAR	Population	Percentage Population Change	Built-up Areas (Km2)	Urban Land Consumption Ratio (ULCR)
2007	2464735	*****	158.23	
2014	2951454	19.75%	330.66	4.09
2024	3739564	26.70%	579.79	2.37
Overall change	+1,274,829	51.72%	+421.56	3.12

Source: Author, 2025.

Note: ***** indicates the start year, where there is no cumulative value.

Characterisation of forest structure by fusing multi-frequency SAR and spaceborne LiDAR.

Radar Vegetation Index (RVI) derived from multi-frequency ALOS PALSAR data was evaluated for the period 2007–2024 (Figure 4). The temporal profile shows a gradual decline over the study period, following a negative linear trend ($y = -0.0005x + 0.8467$). RVI values ranged from approximately 0.85 to 0.88, peaking around 2015 (~0.88) before decreasing steadily to about 0.85 by 2024. The time series indicates a progressive downward shift in RVI values in the latter part of the study period (post-2014), with reduced variability compared to earlier years.

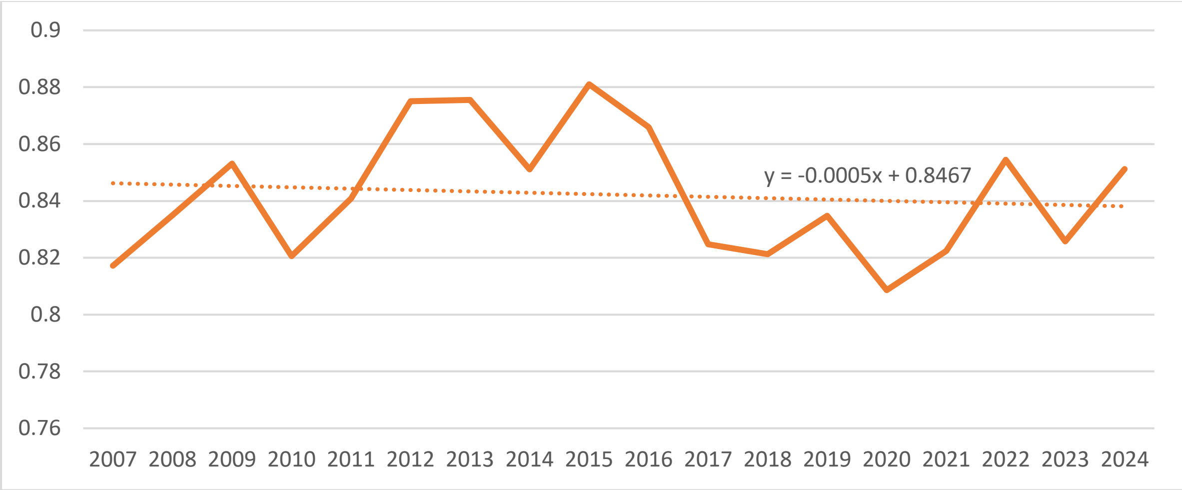

Figure 4: Average Annual Radar Vegetation index from 2007 to 2024.

The spatial distribution of canopy height derived from the GEDI-calibrated CHM is presented in Figure 5. In 2020, the landscape is dominated by the Secondary Canopy class (5–10 m), with widespread occurrence of the >10 m class, particularly in the western and southern parts of the study area (e.g., around Ijero and Efon Alaaye). The <5 m class is present but spatially limited.

By 2025, the spatial distribution of canopy height classes shows a different pattern. The extent of the >10 m class is reduced relative to 2020, while the 5–10 m class appears more fragmented. The <5 m class increases in spatial coverage and is distributed across larger portions of the central and northern regions.

Overall, the maps show a redistribution of canopy height classes between 2020 and 2025, with reduced spatial continuity of higher canopy classes and increased presence of lower canopy height classes.

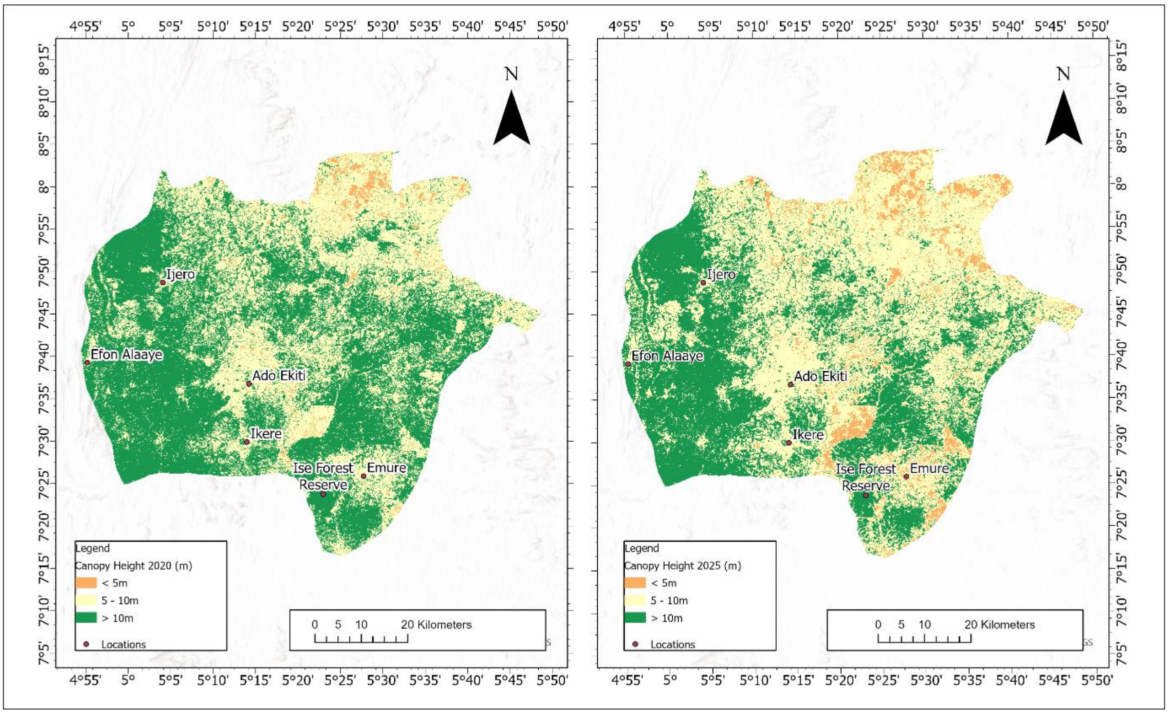

Figure 5: Spatiotemporal Evolution of Canopy Height in Ekiti State (2020–2025)

The integration of spaceborne LiDAR from the Global Ecosystem Dynamics Investigation was used to derive canopy height metrics for Ekiti State for 2020 and 2025. The results indicate measurable differences in canopy height distribution between the two periods.

In 2020, canopy height ranged from 2.73 m to 34.15 m, with a mean value of 10.60 m. In 2025, canopy height ranged from 2.35 m to 27.89 m, with a mean value of 9.34 m.

The maximum canopy height decreased from 34.15 m in 2020 to 27.89 m in 2025, while the minimum canopy height decreased slightly from 2.73 m to 2.35 m. The mean canopy height declined from 10.60 m to 9.34 m, representing a reduction of approximately 1.26 m over the study period.

Threshold-based structural validation of LULC-derived forest extent using GEDI LiDAR (2020–2025)

Structural validation revealed strong sensitivity to canopy height thresholds and temporal dynamics (Table 5). At the 5 m threshold, agreement between LULC-derived forest extent and CHM was consistently low, with F1-scores of 0.581 (2020) and 0.497 (2025), driven by low recall (<0.41), indicating substantial omission of structurally defined forest. In contrast, the 10 m threshold yielded higher agreement (F1 = 0.745 in 2020; 0.662 in 2025), suggesting improved alignment with spectrally derived forest extent.

A consistent decline in F1-score across both thresholds indicates increasing divergence between spectral classification and structural forest definition over time. Notably, overall accuracy remained relatively stable (~0.76 at the 10 m threshold), highlighting its limitation in capturing structural inconsistencies.

Table 5: Table Structural validation metrics for LULC-derived forest extent using canopy height thresholds (5 m and 10 m) for 2020 and 2025

Year	Threshold(m)	Precision	Recall	F1-score	Overall Accuracy
2020	5	0.999	0.410	0.581	0.428
2020	10	0.877	0.647	0.745	0.761
2025	5	0.995	0.331	0.497	0.397
2025	10	0.776	0.578	0.662	0.763

Structural validation metrics comparing LULC-derived forest extent with GEDI-derived canopy height thresholds (≥5 m and ≥10 m) for 2020 and 2025. Results demonstrate strong sensitivity to threshold selection and a temporal decline in spectral–structural agreement, particularly reflected in F1-score and recall, while overall accuracy remains relatively stable at the 10 m threshold.

Anthropogenic Drivers of Vegetation Health and Structural Collapse

The drivers underpinning the observed landscape transitions in Ekiti State, Nigeria were examined. The interactions among demographic pressure, built-up intensity, vegetation health, and forest structure were examined. The results reveal a complex spectral–structural decoupling, here termed a "Spectral–Structural Paradox," arising from divergent anthropogenic influences.

The effect of urbanisation (NDBI) and Demography (Population) on vegetation health.

There is a strong negative association between the Normalised Difference Built-up Index (NDBI) and Normalised Difference Vegetation Index (NDVI) ($\tau = -0.7124, p < 0.05$). The Kendall's Tau correlation analysis identifies urban expansion as the dominant plausible driver of ecosystem degradation of vegetation health. This relationship suggests that as built-up area expands, there is a consistent and measurable decline in the spectral signature of healthy vegetation across the landscape.

The Ordinary Least Squares (OLS) regression further substantiates that NDBI is a significant negative predictor of vegetation health $(\beta = -0.687, p = 0.010, Adj. R^2 = 0.30)$, which aligns with previous findings by Bejide and Olaniran (2026).

In contrast, population density exhibits no statistically significant relationship with forest structure ($p > 0.05$). This demographic–environmental decoupling suggests that forest degradation in Ekiti State is not primarily driven by localized population pressure, but rather by land-use dynamics such as low-density horizontal urban sprawl, speculative land clearing, and infrastructure expansion that exceed actual population growth rates.

Anthropogenic drivers of vegetation health and forest structure

Urbanisation intensity (NDBI) shows a strong negative association with vegetation health (NDVI) ($\tau = -0.7124$, $p < 0.05$) and a moderate negative association with forest structural integrity (RVI) ($\tau = -0.3072$, $p < 0.05$). Ordinary Least Squares regression indicates that NDBI is a significant negative predictor of ecosystem condition ($\beta = -0.687$, $p = 0.010$, Adj. $R^2 = 0.30$). In contrast, population density shows no statistically significant relationship with forest structure ($p > 0.05$), with a negligible association observed between population and RVI ($\tau = -0.0065$). A weak but statistically significant positive relationship is observed between population and NDVI ($\beta = 3.059 \times 10^{-8}$, $p = 0.042$, Adj. $R^2 = 0.834$). The Urban Land Consumption Ratio (ULCR) is 3.12, indicating that built-up area expansion exceeded population growth over the study period.

Discussion

This study evaluated the spatiotemporal impacts of urbanisation and deforestation on forest structure and vegetation condition in Ekiti State, Nigeria, through the integration of multi-sensor SAR (ALOS PALSAR-1/2), optical (Landsat and Sentinel-2), and spaceborne LiDAR (GEDI) datasets. The highlight classifier sensitivity under degraded input conditions and evidence of structurally degraded yet spectrally persistent vegetation.

Algorithm Sensitivity in Multi-Sensor Data Fusion

A significant methodological finding in this study is the extreme disparity in classification performance during the 2007 epoch, where Random Forest (RF) achieved 72.48% accuracy compared to a critically low 29.13% for the Support Vector Machine (SVM). This performance gap highlights a fundamental difference in how these algorithms handle "noisy" multi-sensor stacks. The 2007 dataset was characterized by spectral inconsistencies and spatial discontinuities caused by Landsat 7 SLC-off gaps and the subsequent geostatistical interpolation. SVM, as a global optimizer, attempts to find a single optimal hyperplane to separate classes across the entire feature space. The "noise" introduced by gap-filling likely prevented the SVM from converging on a stable decision boundary, resulting in a substantial reduction in classification performance, with accuracy falling well below that of the Random Forest model.

In contrast, Random Forest proved resilient because of its ensemble architecture. By building numerous decision trees on random subsets of both data and features, RF was able to "ignore" noisy or interpolated predictors in individual trees, allowing the aggregate majority vote to maintain a respectable accuracy of 72.48%. This reinforces that for historical LULC mapping in tropical regions where data is often degraded, ensemble-based learners are generally more robust under degraded data conditions.

From Established Deforestation to Structural Degradation in Ekiti State

The forest decline observed in this study—from 2,131.03 km² in 2007 to 1,590.93 km² in 2024 (−25.34%; 54,010 ha loss)—is consistent with a long-documented trajectory of environmental change within Ekiti State. Earlier studies have repeatedly identified deforestation as a major environmental challenge driven by agricultural expansion and unregulated urban growth.

For instance, Festus estimated that forest cover had already declined to approximately 1,983.95 km² (37.87%) of the state's land area due to anthropogenic pressures. Long-term analyses by Olorunfemi et al. further demonstrated a 51.25% reduction in forest land between 1972 and 2017, confirming that forest depletion in Ekiti is a sustained, multi-decadal process.

At a finer spatial scale, Adeoye and Ayeni reported a loss of 53,469.23 hectares over 25 years in Ijesa Ekiti, while also documenting local perceptions of ecological change, including the disappearance of key timber species such as *Milicia excelsa*, *Terminalia superba*, *Antiaris africana*, and *Gmelina arborea*, alongside increasing ambient temperatures.

Urbanization studies further reinforce this trajectory. Esan and Babalola observed that rapid expansion of built-up areas in Ado Ekiti has driven the conversion of forests and green spaces, with development extending toward peri-urban fringes and outpacing planning controls.

While these studies collectively establish the extent and drivers of horizontal deforestation, they remain largely limited to two-dimensional (areal) assessments. The present study advances this body of knowledge by incorporating GEDI-derived vertical structure, revealing that forest degradation in Ekiti State extends beyond areal loss to include widespread structural collapse within remaining forest patches.

Canopy height dynamics and structural degradation

The canopy height results indicate a decline in forest structural condition in Ekiti State between 2020 and 2025. Mean canopy height decreased from 10.60 m to 9.34 m, accompanied by reductions in maximum height, suggesting a loss of vertical complexity within the landscape.

This trend is consistent with broader regional findings. A complementary regional analysis (Bejide et al., 2026, preprint) reported a decline in mean canopy height in Ekiti State from 10.30 m to 8.15 m. Although the magnitude differs, both analyses indicate a consistent downward trend in forest structure. The variation is likely due to differences in spatial resolution and modelling approaches.

Overall, the results indicate progressive structural degradation, where reductions in canopy height occur without complete loss of vegetation cover. This highlights the importance of integrating LiDAR-derived metrics to capture changes in forest condition that are not detectable using spectral data alone.

From Horizontal Deforestation to Vertical Degradation

While land-cover statistics quantify horizontal (two-dimensional) forest change, the integration of spaceborne LiDAR from the Global Ecosystem Dynamics Investigation reveals an additional vertical dimension of forest condition. Structural validation indicates that agreement between LULC-derived forest extent and canopy height–based definitions is both threshold-dependent and temporally variable.

At the 5 m threshold, agreement was low (F1 = 0.581 in 2020; 0.497 in 2025), reflecting substantial omission of structurally defined forest. Increasing the threshold to 10 m improved agreement (F1 = 0.745 in 2020; 0.662 in 2025), although a decline in F1-score over time indicates increasing divergence between spectral classification and structural forest representation.

This discrepancy reflects the limitation of spectral indices, which capture canopy greenness but not vertical structure. Consequently, areas classified as forest may include low-stature or structurally simplified vegetation. These findings indicate that forest change in Ekiti State involves not only areal loss but also progressive structural degradation within remaining forested areas.

Uncertainty in GEDI-Derived Structural Metrics

While GEDI provides critical vertical insights, its performance is context-dependent. In structurally homogeneous systems such as Eucalyptus plantations in Brazil, GEDI-derived RH metrics explain up to 93% of canopy height variability. However, Ekiti’s fragmented forest–savanna mosaic introduces significant uncertainty due to canopy heterogeneity, terrain effects, and geolocation offsets.

Recent work by Cho et al. in the Democratic Republic of Congo reports relative RMSE values of up to 33% in GEDI height estimates under similar tropical conditions. This highlights that while GEDI is indispensable for structural assessment, its outputs must be interpreted cautiously in complex African landscapes.

Threshold Sensitivity and Recall Imbalance

The validation of spectral LULC maps against GEDI LiDAR revealed a significant Recall imbalance, particularly at the 5 m canopy height threshold. While the spectral maps showed near-perfect Precision (>0.99), the Recall was critically low (<0.41). This implies that while the spectral classification is highly accurate when it does identify a forest, it fails to detect a substantial proportion (approximately 60–67%) of the structurally valid forest extent in the landscape. This "under-mapping" occurs because regenerating forests or low-stature woodlands (5–10 m height) often possess spectral signatures that overlap with shrubland or agricultural land, causing them to be omitted from traditional forest masks. However, as the threshold is increased to 10 m, the agreement improves (F1 = 0.745 in 2020), suggesting that spectral sensors are only reliable at capturing high-stature, mature forest blocks. The widening gap between spectral "greenness" and structural height, evidenced by the declining F1-score between 2020 and 2025—confirms that the landscape is entering a phase of spectral–structural decoupling.

Urban Expansion as the Dominant Driver of Landscape Transformation

The observed environmental changes are closely linked to the dynamics of urban expansion. Between 2007 and 2024, Ekiti State’s population increased by 51.72%, while built-up area expanded by 266.42%, resulting in an Urban Land Consumption Ratio (ULCR) of 3.12. This indicates that land consumption has outpaced population growth by more than threefold, reflecting spatially inefficient urban expansion.

This pattern is consistent with global observations that urban land expansion frequently exceeds population growth rates (Seto et al.,2012; Angel et al.,2010). In Ekiti State, this imbalance is further reflected in the 58.59% decline in urban population density, indicating a shift toward low-density, horizontally expansive development.

The spatial consequences of this expansion are evident in the displacement of over 54,000 hectares of forest, alongside increasing fragmentation of remaining vegetation. These findings indicate that urban expansion is a dominant contributor to landscape transformation, influencing both areal forest loss and structural degradation.

The Demographic–Environmental Paradox: Decoupling Population from Structural Loss

A counter-intuitive result of this study is the absence of a statistically significant relationship ($p > 0.05$) between population density and forest structure, despite a 51.72% increase in the state's population. Traditionally, demographic growth is viewed as the primary driver of forest loss; however, our results suggest a distinct "Population–Forest Decoupling" in Ekiti State.

This decoupling is empirically supported by the Urban Land Consumption Ratio (ULCR) of 3.12. This value reveals that built-up area expanded more than three times faster than the population grew. This suggests the presence of anticipatory or speculative land development processes, where vast tracts of forest are cleared and subdivided into plots long before actual human settlement occurs. Consequently, the structural collapse of the forest is more closely correlated with built-up intensity (NDBI) ($\tau = -0.3072$) than with localized population pressure

Conclusion

This study demonstrates the value of integrating multi-sensor SAR, optical, and spaceborne LiDAR (GEDI) data for monitoring complex landscape dynamics in tropical environments. Methodologically, the results show that ensemble classifiers such as Random Forest are robust for historical land-cover mapping under degraded optical conditions, while the inclusion of SAR data improves reliability in cloud-prone regions.

The key finding is the identification of a spectral–structural divergence in forest representation. While horizontal forest loss was quantified at 25.34% (54,010 ha) between 2007 and 2024, structural analysis reveals a concurrent decline in vertical forest condition. Mean canopy height decreased from 10.60 m in 2020 to 9.34 m in 2025, indicating progressive structural degradation within remaining forested areas. This suggests that spectrally "green" landscapes may mask reductions in vertical complexity and biomass.

Furthermore, the results show that inefficient urban expansion is a dominant driver of this change. The Urban Land Consumption Ratio (ULCR) of 3.12 indicates that land conversion has occurred at a rate substantially exceeding population growth, reflecting a pattern of low-density, spatially extensive development. This form of urbanisation is associated with both horizontal forest loss and gradual structural thinning of the landscape.

The combined evidence of declining canopy height, decreasing structural agreement (F1-score), and persistent spectral greenness supports the existence of a "cryptic" degradation phase, in which forest ecosystems undergo structural collapse without immediate spectral manifestation. This decoupling underscores the limitation of relying solely on spectral indicators for forest monitoring in rapidly transforming tropical landscapes.

Implications for Policy

The findings of this study have several implications for sustainable land management and forest monitoring in Nigeria. First, the observed discrepancies between spectral classification and GEDI-derived canopy height indicate the need to integrate structural (3D) metrics into national forest monitoring frameworks. Reliance on areal (2D) assessments alone may lead to misrepresentation of forest condition and associated carbon estimates, particularly in degraded tropical landscapes.

Second, the high Urban Land Consumption Ratio (ULCR = 3.12) highlights a pattern of spatially inefficient urban expansion. This suggests the need for planning approaches that limit horizontal sprawl and improve land-use efficiency, particularly in rapidly growing peri-urban areas where forest conversion is most pronounced.

Third, the decline in canopy height and increasing spectral–structural divergence indicates that forest degradation in Ekiti State extends beyond areal loss. This underscores the importance of management strategies that prioritise structural recovery and ecosystem integrity, rather than focusing solely on maintaining or increasing vegetation cover.

Finally, the demonstrated utility of multi-sensor integration suggests that combining SAR, optical, and LiDAR data can support improved monitoring of forest change. Such approaches may enhance early detection of structural degradation and provide more reliable information for land-use planning and conservation interventions.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used Google Gemini for language and grammatical accuracy correction. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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