Spectral–Structural Divergence in Forest Extent under Land-Use Change: Threshold-Based Assessment Using GEDI LiDAR in Ekiti State, Nigeria

Oluwafemi David Bejide[1]*, Ojo Davies Ajewole[2], Kunle David Emiola[2], Hezekiah Daramola Olaniran[1].

[1] Department of Geography, University of Ibadan, Ibadan, Nigeria

[2] Department of Geography, University of Ilorin, Ilorin, Nigeria

*Corresponding author:

Oluwafemi David Bejide

Email: Obejide9198@stu.ui.edu.ng

ORCID: 0009-0002-4588-0315

Ojo Davies Ajewole

Email: Ajewole.od@unilorin.edu.ng

ORCID: 0009-0007-3577-3467

Kunle David Emiola

kunledavid15@hotmail.com

ORCID: 0009-0008-9133-3885

Hezekiah Daramola Olaniran

Email: hd.olaniran@mail.ui.edu.ng

ORCID: 0000-0001-5751-596X

This manuscript is currently under review in *Environmental Monitoring and Assessment*.

Abstract

Forest degradation is often underestimated because conventional spectral indicators fail to capture vertical forest structure adequately. This study presents a threshold-based spectral–structural assessment that evaluates agreement between Land use/land cover (LULC)-derived forest extent and GEDI LiDAR-informed canopy height model (CHM)-derived forest extent using FAO forest definition ≥0.5 ha and canopy height thresholds of ≥5 m and ≥10 m in Ekiti State, Nigeria.

LULC dynamics between 2007 and 2025 were modelled using a random forest classifier and multi-sensor fusion of Synthetic Aperture Radar datasets (Sentinel-1 and ALOS PALSAR) and optical imagery (Landsat and Sentinel-2). Overall classification accuracies were 72.48%, 75.93%, and 82.35% in the 2007, 2015, and 2025 epochs, respectively. The forest cover declined by 724 km² (33.01%), while built-up area increased by 266.42 km² (270.33%).

The canopy height model developed from multi-sensor predictors achieved R^2 values of 0.35 (2020) and 0.41 (2025). The mean canopy height in Ekiti State decreased from 10.60 ± 3.42 m in 2020 to 9.34 ± 3.48 m in 2025.

Agreement between LULC-derived forest extent and CHM-derived forest extent was assessed using two canopy height thresholds (≥5 m and ≥10 m). The 5 m threshold was consistently low (F1 = 0.573 in 2020; 0.459 in 2025), while the 10 m threshold yielded higher agreement (F1 = 0.748 in 2020; 0.695 in 2025). These findings demonstrate that spectral forest extent alone is insufficient to represent forest structural condition. This study proposes a spectral–structural framework integrating LiDAR, optical, and SAR for monitoring, degradation assessment, and planning.

Keywords: Multi-sensor fusion, GEDI LiDAR, Deforestation monitoring, Canopy height model (CHM), Land-use change

1. Introduction

Monitoring tropical forest loss under accelerating land use and land cover changes requires more than two-dimensional spectral data, particularly in rapidly changing tropical landscapes where agriculture, urban expansion and other anthropogenic activities continue to transform the forest ecosystem. The assessment of the state of tropical forests in Africa has been difficult due to their complex structure, great biodiversity, and spatial variability. While advancements in multi-sensor remote sensing and machine learning methods have led to significant improvements in mapping forest attributes using optical, radar, and LiDAR data, questions remain about how to accurately characterise the vertical structure and degradation of forests using spectral analysis alone (Bossy et al., 2025).

Nigeria has experienced substantial forest loss due to expansion of agriculture and built-up areas, which contributes to biodiversity decline and ecosystem degradation (Fasona et al., 2022). According to the Federal Ministry of Environment and Federal Department of Forestry (2026), factors that lead to deforestation in Nigeria are land use change resulting from agricultural expansion, particularly in savanna and lowland forest zones.

These pressures are particularly evident in Ekiti State, located in the transition zone between the forest and savanna zone, where previous land-use/land-cover studies reported a 51.25% decline in forest cover between 1972 and

2017, primarily due to agricultural expansion and urban growth (Olorunfemi et al., 2020). Earlier studies also identified logging, fuelwood extraction, and road development as major drivers of forest degradation within the state (Festus, 2012). As noted by Güneralp et al. (2017), encroachments resulting from urbanisation and the demands of a growing population have direct and indirect consequences for the natural ecosystems in Africa. Consequently, the continued transformation of forest landscapes in Ekiti State highlights the need for ecosystem sustainability and forest monitoring.

Remote sensing technologies have become central to the assessment of vegetation dynamics and land-cover change at regional and global scales. Optical satellite systems such as Landsat and Sentinel-2 are widely used to monitor vegetation condition using spectral indices, including the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), enabling long-term evaluation of deforestation and vegetation change (Hansen et al., 2013). In tropical environments characterised by persistent cloud cover, Synthetic Aperture Radar (SAR) datasets such as Sentinel-1 and ALOS PALSAR provide additional advantages through all-weather imaging capability and sensitivity to vegetation structure and surface roughness (Hosseiny et al., 2024). Consequently, the integration of optical and SAR datasets has improved the detection of urban expansion, forest disturbance, and landscape transformation in heterogeneous tropical environments (Hosseiny et al., 2024; Mullissa et al., 2024).

Despite these advances, conventional forest monitoring approaches remain strongly dependent on spectral representations of vegetation cover. Spectral indices primarily respond to canopy surface reflectance and may saturate in densely vegetated environments, limiting their ability to represent vertical ecosystem characteristics such as canopy height, biomass distribution, and structural complexity (Potapov et al., 2021). Under such conditions, degraded forests may continue to exhibit strong vegetation signatures despite substantial declines in structural integrity. Processes including selective logging, fuelwood extraction, fragmentation, and canopy thinning may alter forest structure before major spectral changes become detectable (Gao et al., 2020). Consequently, some landscapes may remain classified as forest in conventional land-cover products despite undergoing significant structural degradation.

This limitation highlights an important source of uncertainty in remote sensing-based forest assessment. In many cases, the dominant uncertainty is not necessarily overall classification accuracy, but rather the inability of two-dimensional spectral observations to adequately represent three-dimensional ecosystem structure. As a result, spectrally derived forest extent may not always correspond to actual ecological conditions, particularly in rapidly urbanising tropical environments where disturbances frequently affect vertical canopy organisation without immediately altering horizontal vegetation cover. The growing discrepancy between spectrally mapped forest extent and structurally defined forest condition highlights a major limitation in conventional forest monitoring frameworks (Gao et al., 2020; Mbow et al., 2015).

International forest monitoring frameworks emphasise structural characteristics in defining forest extent and ecological condition. According to the Food and Agriculture Organisation (FAO, 2018), forests are characterised by trees capable of reaching a minimum height of 5 m in situ, alongside minimum canopy cover requirements and the absence of dominant non-forest land uses. This definition highlights the importance of vertical vegetation structure in distinguishing forests from shrublands, degraded vegetation systems, and other low-stature land-cover classes. However, most conventional classifications derived from optical and SAR imagery primarily represent horizontal vegetation characteristics and do not directly evaluate canopy height or structural integrity. Consequently, areas identified as forest in spectral classifications may not necessarily satisfy structurally defined forest conditions.

Recent developments in spaceborne Light Detection and Ranging (LiDAR), particularly the Global Ecosystem Dynamics Investigation (GEDI), provide new opportunities for directly assessing vertical forest structure through measurements of canopy height and vegetation profiles (Potapov et al., 2021; Fayad et al., 2021). Integrating GEDI observations with optical and SAR datasets, therefore, enables a more comprehensive evaluation of forest condition by linking horizontal forest extent with vertical structural information. However, relatively few studies in tropical Africa have quantitatively assessed the reliability of spectrally derived forest extent using independent structural observations within rapidly urbanising landscapes.

This study evaluates the reliability of spectrally derived forest extent in Ekiti State, Nigeria, by integrating multi-sensor remote sensing datasets with GEDI-derived canopy height information. A threshold-based structural validation framework employing canopy height thresholds of ≥5 m and ≥10 m was developed to quantify agreement between spectral forest classification and structurally defined forest conditions across time. By comparing two-dimensional spectral forest representation with LiDAR-derived three-dimensional canopy structure, the study provides an empirical assessment of spectral–structural divergence under continued land use change. This study sought to address the following research questions:

RQ1: How has land-use/land-cover change affected forest extent in Ekiti State, Nigeria, between 2007 and 2025?

RQ2: How effectively can GEDI LiDAR integrate with multi-sensor optical, SAR, and terrain predictors to estimate canopy height in Ekiti State?

RQ3: To what extent does the agreement between spectrally derived forest extent and structurally defined forest extent vary under different canopy-height thresholds (≥5 m and ≥10 m) in Ekiti State?

2. Study Area

The study focuses on Ekiti State, located in south-western Nigeria within the latitudes 7°15′N–8°05′N and longitudes 4°45′E–5°45′E (Adegboyega & Adebayo, 2018). Ekiti State is bounded to the north and north-east by Kwara and Kogi, to the east and south by Ondo State, and to the west by Osun State, as shown in Fig. 1. The state spans approximately 5,435 km² and functions as a transition zone between the humid southern rainforest and the northern Guinea savanna. It is characterised by a tropical climate, with mean annual rainfall of about 1,200 mm and temperatures ranging from 27–32°C. This diverse ecological landscape is administered through 16 Local Government Areas, with the administrative capital, Ado-Ekiti, serving as the primary hub of urban expansion. Since 2006, the state has undergone a significant demographic shift, with the population growing from 2.38 million to a projected 3.69 million by 2023 (NPC, 2022), placing unprecedented demand on local forest resources and land availability.

Ekiti State lies within a rainforest–Guinea savanna ecological transition zone, making it highly sensitive to both climate variability and anthropogenic land-use change. This transitional setting provides a gradient of forest conditions, ranging from relatively intact moist forest in the south to more degraded and fragmented landscapes in the north. More importantly, findings have shown that several land-use activities, including urban growth, timber exploitation, illegal lumbering, fuel extraction, road construction, intensive agricultural practices, and population growth, lead to depletion of forest cover in the state (Adeoye & Ayeni, 2011; Festus, 2012; Olorunfemi et al., 2020). These characteristics make Ekiti State a suitable and representative study area for evaluating forest extent and structural change under land-use pressure.

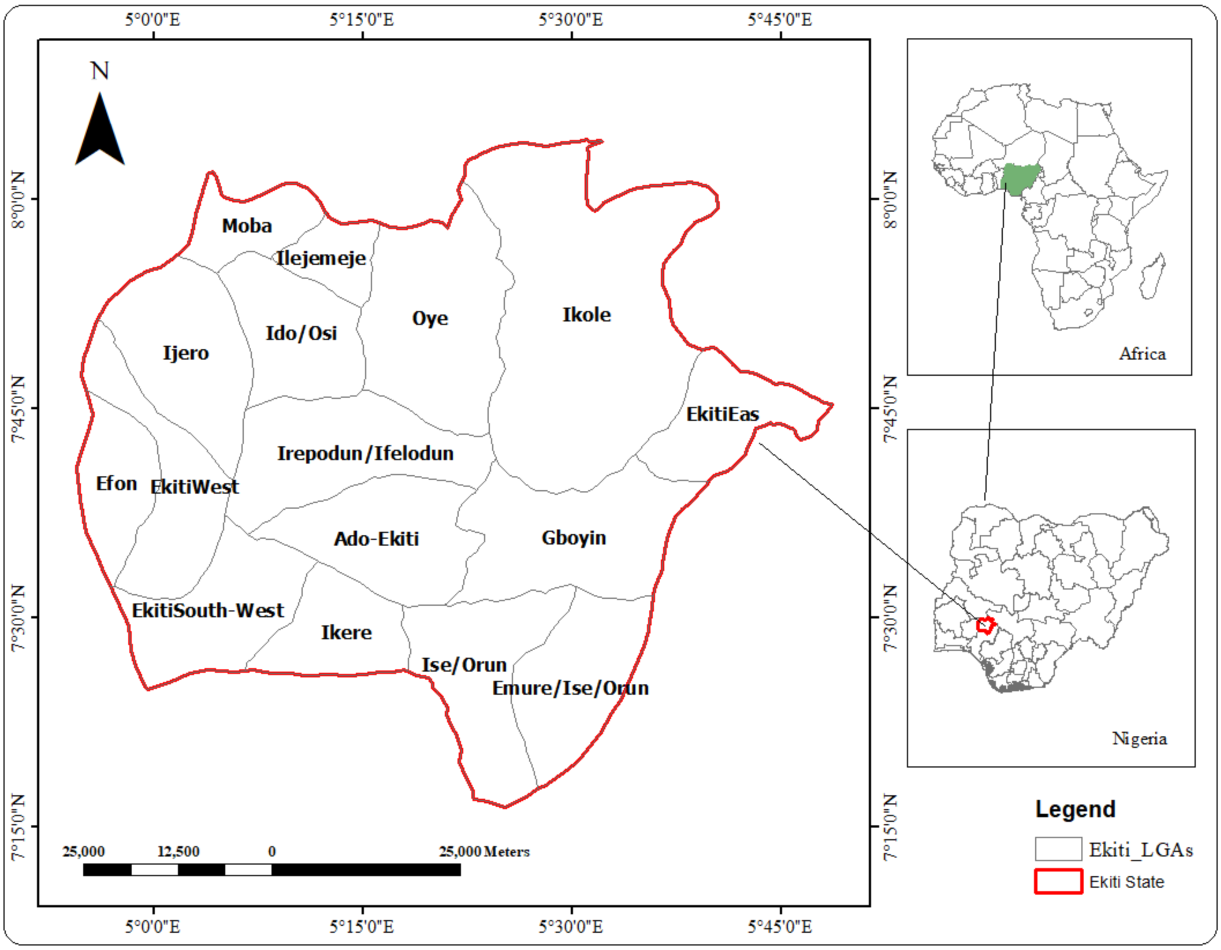

Fig. 1: Ekiti State, Nigeria

3. **Methodology**

This study utilised multi-sensor remote sensing datasets and demographic data to evaluate land-cover change and forest structural dynamics in Ekiti State, Nigeria. Satellite datasets included Landsat 7 ETM+, Landsat 8, Sentinel-1 SAR, Sentinel-2 optical imagery, ALOS PALSAR, SRTM DEM, ESA WorldCover, and GEDI Level 2A product (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 sources and analytical roles

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	NASA LP DAAC	25m	Vertical canopy profile and RH98 height calibration

Note: All data were resampled to 30m resolution using nearest neighbour before prediction and map production

Table 2: Multi-sensor datasets and predictor variables used for LULC classification and canopy height modelling

Category	Variable(s)	Source	Application	Functional role in modelling
Optical	Blue, Green, Red, NIR, SWIR1, SWIR2	Landsat7/8	LULC	Spectral discrimination of land-cover classes
Optical (Sentinel-2)	B2, B3, B4, B8, B11, B12	Sentinel-2	CHM	Spectral reflectance; vegetation and moisture sensitivity
Vegetation Indices	NDVI, NDMI, NBR	Derived from S2	CHM/LULC	Canopy greenness, moisture, disturbance detection
SAR backscatter	VV, VH (Sentinel-1); HH/HV (PALSAR)	Sentinel-1, PALSAR	CHM/LULC	Structural information, canopy penetration
SAR Derived Metrics	Backscatter ratios (VV/VH, HH/HV, RVI, GLCM texture metrics)	Sentinel-1 PALSAR	CHM/LULC	Canopy density and structural complexity
Terrain	Elevation, Slope, TWI	SRTM DEM	CHM/LULC	Topography controls vegetation distribution

Note: NIR = Near Infrared; SWIR = Shortwave Infrared; NDVI = Normalised Difference Vegetation Index; NDMI = Normalised Difference Moisture Index; NBR = Normalised Burn Ratio; VV, VH, HH and HV = radar backscatter polarisations; RVI = Radar Vegetation Index; GLCM = Grey-Level Co-occurrence Matrix; TWI = Topographic Wetness Index.

Predictor availability and use varied according to the modelling task and observation period; consequently, not all variables listed were included in every LULC or canopy-height model.

3.1. Land use and land cover changes in Ekiti State

Land use/land cover classification was conducted within the Google Earth Engine (GEE) environment using a multi-sensor integration approach. To minimise cloud contamination and Landsat 7 SLC-off effects during the 2007 epoch, Landsat imagery was combined with ALOS PALSAR L-band SAR data. Landsat imagery was processed as a cloud-masked median composite, while SAR imagery was filtered using a focal median filter.

A multi-sensor predictor stack comprising multispectral bands, SAR backscatter (HH and HV), Radar Vegetation Index (RVI), and SRTM-derived slope was developed to improve class separability. All datasets had different spatial resolutions. To ensure spatial consistency across the multi-sensor predictor stack, Landsat (30 m) was adopted as the reference resolution, and all other predictor variables were resampled to 30 m using the nearest-neighbour method. Nearest-neighbour resampling was selected to preserve the original pixel values of the predictor variables.

Predictor availability varied across the study period depending on sensor availability (e.g., Landsat 7 and ALOS PALSAR for 2007, and Landsat 8 and Sentinel-2 for subsequent epochs); therefore, not all predictor variables were included in every LULC.

Random Forest (RF) classifier was applied using manually digitised training samples representing six land-cover classes: water, barren land, built-up area, agriculture, shrubland, and forest. Classification accuracy was evaluated using confusion matrix metrics, including overall accuracy and Kappa coefficient, based on a 70% training and 30% validation split.

Many land use land cover classification studies rely primarily on optical sensors for LULC prediction. In contrast, this study integrated the terrain and the synthetic aperture radar sensors (Sentinel 1 and ALOS PALSAR) and the terrain features derived from the digital elevation model in the random forest classifier to improve class separability. This integration ensured that the classifier could leverage the spectral, structural and topographic characteristics of the Ekiti State landscape. The integration of multisensory fusion of optical and SAR sensors for LULC mapping is particularly advantageous in the tropical region with persistent high cloud cover (Prudente et al.,2022), while the inclusion of the topographic features was necessary to account for the hilly and rocky terrain that characterises part of Ekiti State.

3.2. Canopy height models (CHMs) for Ekiti State

GEDI Level 2A (GEDI02_A, Version 002) data were downloaded using the Python API for NASA EarthAccess in Google Colab for the 2020 and 2025 observation periods. GEDI granules intersecting the bounding extent of Ekiti State were retrieved, and all available GEDI beams in Ekiti State in each year were considered. Quality control was applied at the footprint level by retaining observations with valid geographic coordinates, a GEDI quality flag of 1 (quality_flag = 1), and a degradation flag of 0 (degrade_flag = 0). The quality-filtered footprints were subsequently spatially intersected with the Ekiti State boundary to remove observations falling outside the study area. RH98 was extracted from the retained GEDI footprints as the response variable for canopy-height modelling.

A total of 42,480 quality-filtered GEDI points were available for 2020, while 18, 298 footprints were available for 2025 (Fig. 2). A total of 18,000 GEDI RH98 points were randomly sampled for canopy height modelling 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) algorithms, utilising an 80/20 train-test split on the training samples (18,000), with data split into training and testing subsets. Specifically, 14,508 points were used to train the model, while an independent, held-out test set of 3,492 points ($n = 3{,}492$) was reserved exclusively for model validation and residual evaluation (Fig. 3).

Model performance was evaluated using standard regression metrics (R^2, RMSE, and MAE). The trained Random Forest models were applied to the multi-sensor predictor stack to generate wall-to-wall canopy height maps at 30 m spatial resolution, consistent with the resampling approach described in Section 3.1. 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

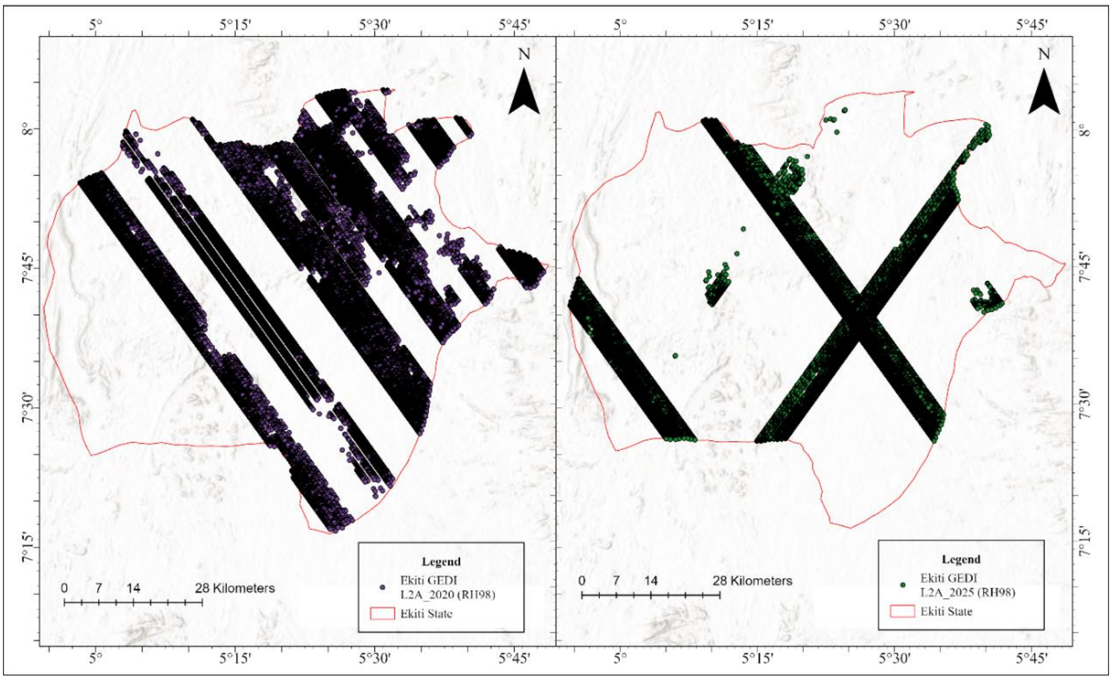

Fig 2: Distribution of GEDI footprints used for canopy height modelling in Ekiti State.

3.3. Threshold-based structural assessment of spectral–structural divergence in forest extent

Canopy height data derived from the Global Ecosystem Dynamics Investigation (GEDI) were used to delineate structurally defined forest extent. The CHM- and LULC-derived forest maps for 2020 and 2025 were reclassified into binary forest masks (forest = 1; non-forest = 0). To ensure spatial consistency between the spectral and structural forest definitions, an eight-neighbour connectivity rule was used to identify contiguous forest patches, and a minimum patch-area criterion of >0.5 ha was applied to both the LULC- and CHM-derived forest masks. Patches below this threshold were excluded from subsequent spectral–structural comparison.

The structural validation was limited to 2020 and 2025 because GEDI observations were only available from 2019 onwards. The year 2020 was selected as the earliest year with corresponding LULC data for spectral–structural comparison, while 2025 represented the most recent observation period. Consequently, corresponding LULC maps and canopy height models for 2020 and 2025 were used for structural validation

Both LULC_derived forest extent and GEDI_informed canopy height structural forest extent were evaluated using two canopy-height thresholds: ≥5 m, corresponding to the FAO minimum tree-height criterion, and ≥10 m, representing a stricter structural threshold used to assess the sensitivity of spectral–structural agreement to canopy-height definition. The 10m threshold was selected because it is more representative of mature tropical forest structure. The >0.5-ha minimum contiguous-area criterion was maintained under both canopy-height thresholds, ensuring that canopy height was the principal structural criterion varied in the sensitivity assessment.

Pixel-wise overlays between the filtered LULC-derived spectral forest masks and CHM-derived structural forest masks were performed for each epoch and canopy-height threshold. The overlays were used to derive true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN), from which precision, recall, F1-score, and overall accuracy were calculated. Differences in F1-score and recall between the ≥5 m and ≥10 m thresholds were used to evaluate the sensitivity of spectral–structural agreement to canopy-height definition and its temporal variation between 2020 and 2025

4. Results

4.1. 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 0.41 for 2025 (Fig. 3). The model achieved RMSE values of 4.46 m and 4.43 m, and MAE values of 3.43 m and 3.44 m for 2020 and 2025, respectively. The relative RMSE for 2020 was 44.04%, while the relative RMSE of 45.60% was recorded in 2025.

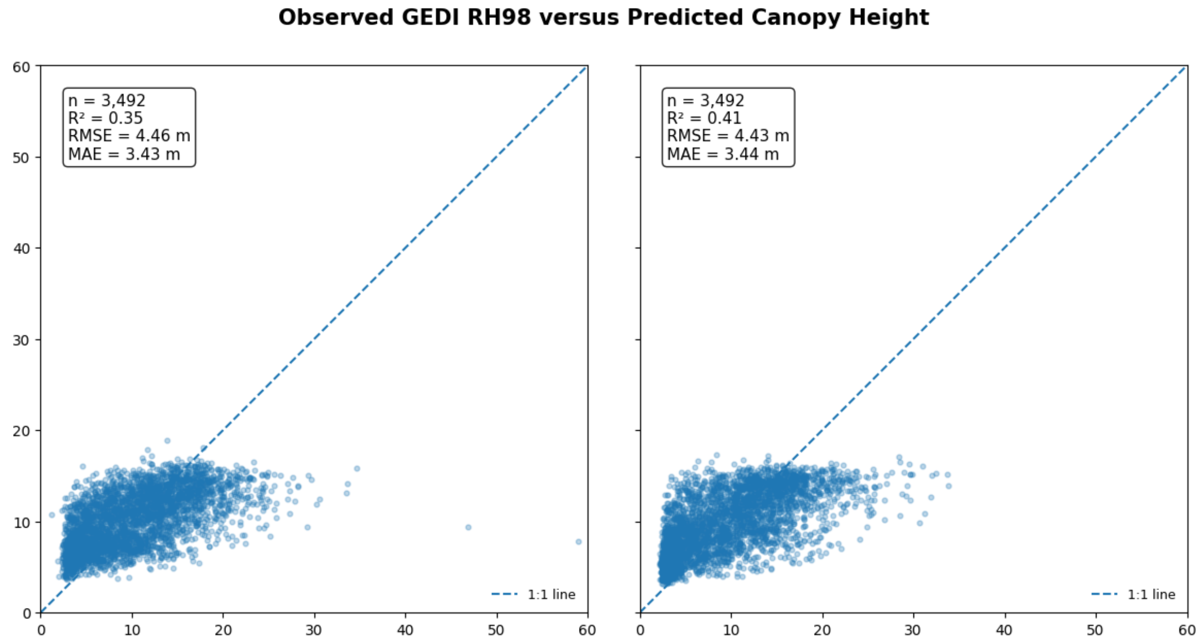

Fig 3: Observed GEDI RH98 versus Random Forest-predicted canopy height for 2020 and 2025

4.2. Feature importance for canopy height modelling

The study performed recursive feature elimination (RFE) to reduce predictor redundancy and retain the most informative variables for the canopy height model. The lists of selected predictors used for the canopy height model for 2020 and 2025 are presented in Fig 4.

In 2020, the optical predictors (NDMI, B11, NDVI, SWIR_ratio), accounted for 37.0% of the predictors; the synthetic aperture radar predictors (S1_VV_dB, P_HV_dB, S1_diff, P_HV_HH_ratio, P_HV_con, P_HH_var) contributed 31.0%, and terrain variables (Elevation, Slope) accounted for 10%. Derived interaction variables (SAR_NDMI, Elev_NDMI, and Elev_Slope) represented the remaining 25.0% of the total predictor importance.

In 2025, optical predictors (B11, B12, NBR, NDMI, and NDVI) accounted for 50.4% of the total predictor importance. SAR predictors (S1_VV_dB, S1_VH_VV_ratio, S1_diff, P_HV_dB, SAR_sum, P_HH_con, and P_HV_var) contributed 35.6%, whereas terrain variables (elevation and slope) accounted for 9.3%. The remaining 4.3% was contributed by the derived interaction variable (Elev_Slope). Collectively, the retained predictor groups demonstrate the complementary roles of optical, SAR, terrain, and interaction variables in modelling canopy height across the study area.

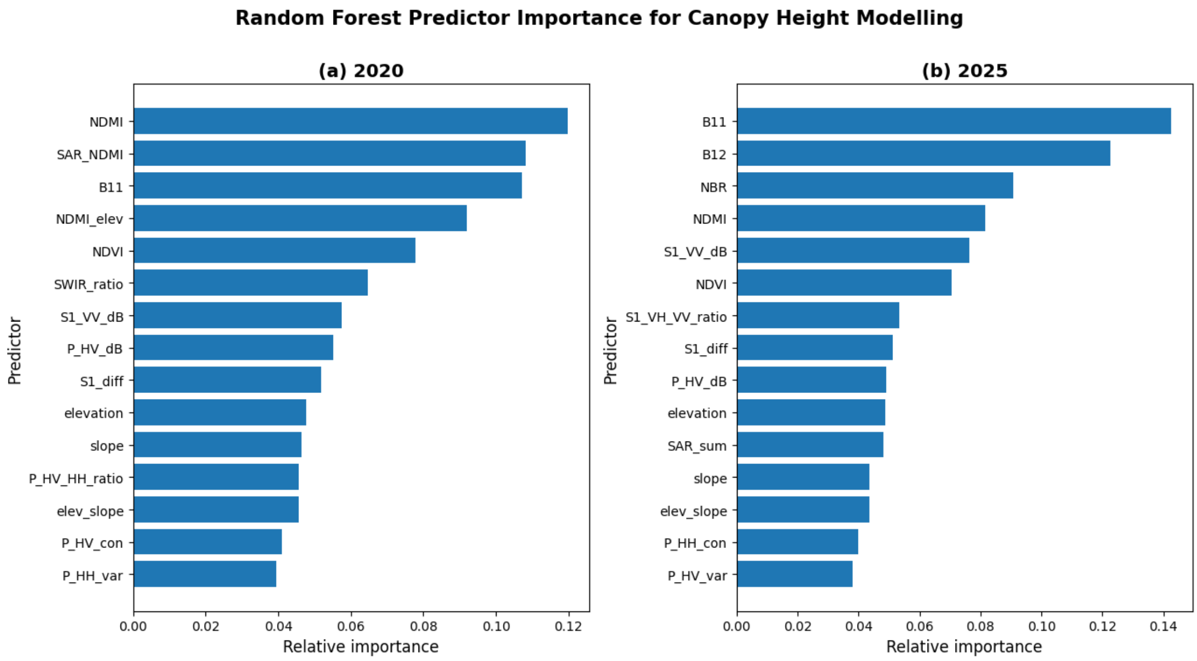

Fig 4: Feature importance of Canopy height predictors for 2020 and 2025

4.3. Land use and land cover performances

The classification performance for land use and land cover in the 2007, 2015, and 2025 epochs using the random forest classifier was 72.48%, 75.93%, and 82.35%, with corresponding Kappa coefficients of 66.2%, 70.0%, and 75.3%, respectively. The producer's and user's accuracy for each land use type across 2007 to 2025 is presented in Table 3. The overall producer accuracy ranged from 46.48% for shrubland in 2007 to 94.12% for water in 2025, while the user accuracy ranged from 50.65% for shrubland in 2015 to 100.00% for water in both 2007 and 2015.

Built-up areas recorded producer's accuracies of 87.70%, 92.06%, and 92.90%, and user's accuracies of 86.29%, 87.22%, and 89.71% for 2007, 2015 and 2025 epochs, respectively. The forest also exhibited producer's accuracies of 77.08%, 82.61%, and 78.26% with user accuracy of 67.27%, 76.00%, and 72.00%, across 2007, 2015 and 2025 epochs.

Table 3: Producer's accuracy (PA) and user's accuracy (UA) for each land use/land cover class across the 2007, 2015, and 2025 epochs.

Class	2007 PA/UA	2015 PA/UA	2025 PA/UA
Water	90.00 / 100.00	61.76/ 100.00	94.12 / 94.12
Rocky Outcrops	76.47 / 66.10	74.68 / 84.29	78.26 / 78.26
Built-up	87.70 / 86.29	92.06 / 87.22	92.90 / 89.71
Agriculture	54.76 / 58.23	67.86 / 66.67	75.81 / 82.46
Shrubland	46.48 / 50.77	57.35 / 50.65	47.06 / 51.61
Forest	77.08 / 67.27	82.61 / 76.00	78.26 / 72.00
Overall Accuracy (%)	72.48	75.93	82.35
Kappa	0.662	0.700	0.753

4.4. Predictor importance of the multi-sensor fusion in LULC

The study utilised multiple sensors for the land use land cover classification to include the spectral, structural and terrain characteristics of the Ekiti landscape in the prediction. The importance of the predictors in multi-sensor fusion is shown in Fig. 5. The optical sensors and their derived indices contributed 69.85%, 62.21%, and 59.49% of the importance to the land use/land cover classification, respectively, in the 2007, 2015, and 2025 epochs. The Synthetic Aperture Radar (SAR) sensors contributed 19.24%, 28.81%, and 29.11% to LULC classification, which indicates that structural complexity was a factor in the prediction. The terrain information accounted for 10.91%, 8.97%, and 11.40%, respectively, in the 2007, 2015 and 2025 epochs. This result indicates that

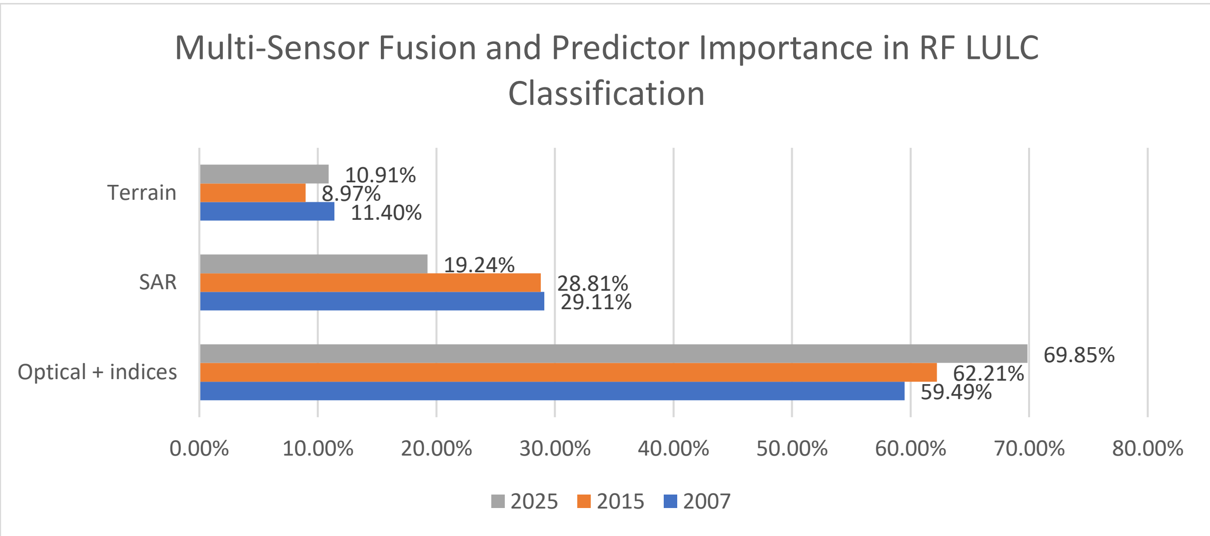

Fig 5: Multi-Sensor Fusion and Predictor Importance in RF LULC Classification

4.5. Land use and land cover changes in Ekiti State from 2007 to 2025

Fig. 6 illustrates the spatial distribution of land use/land cover (LULC) classes in Ekiti State for 2007, 2015, and 2025. Six major classes were identified, including water bodies, rock outcrops, built-up areas, agricultural land, shrubland, and forest.

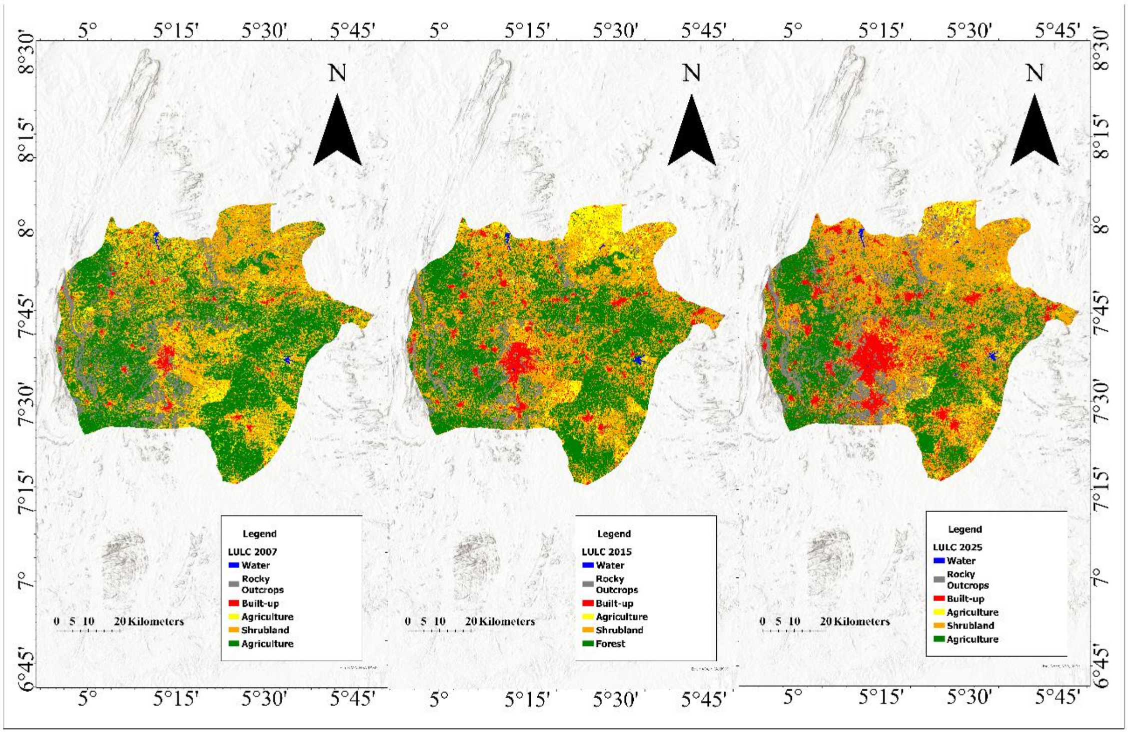

Fig. 6: Land use and land cover 2007, 2015, and 2025.

The areal statistics (Table 4) show substantial land-cover transformation in Ekiti State between 2007 and 2025. Forest and shrubland were the dominant classes in 2007, covering 2193.19 km² and 1577.36 km², respectively, while built-up areas occupied only 167.86 km² and were concentrated around major urban centres.

Built-up areas increased progressively to 330.67 km² in 2015 and 621.63 km² in 2025, representing an overall increase of 270.33%. In contrast, forest cover declined from 2193.19 km² in 2007 to 1469.19 km² in 2025, representing a net loss of approximately 724.00 km² (724,000 hectares). Shrubland showed comparatively smaller changes, increasing slightly to 1738.88 km² by 2025.

Table 4: Area Statistics of Land use and Land Cover changes in Ekiti State from 2007 to 2025

LULC	2007	2015	2025	Percentage Change (%)
Water	7.98	12.29	13.42	68.17%
Rocky Outcrops	639.57	376.11	649.38	1.53%
Built-up	167.86	330.67	621.63	270.33%
Agriculture	728.53	530.56	822.31	12.87%
Shrubland	1577.36	1925.46	1738.88	10.23%
Forest	2193.19	2139.64	1469.19	-33.01%

4.6. Canopy height models (CHMs) for Ekiti State

The spatial distribution of canopy height derived from the GEDI-calibrated CHM is presented in Fig. 7. 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.

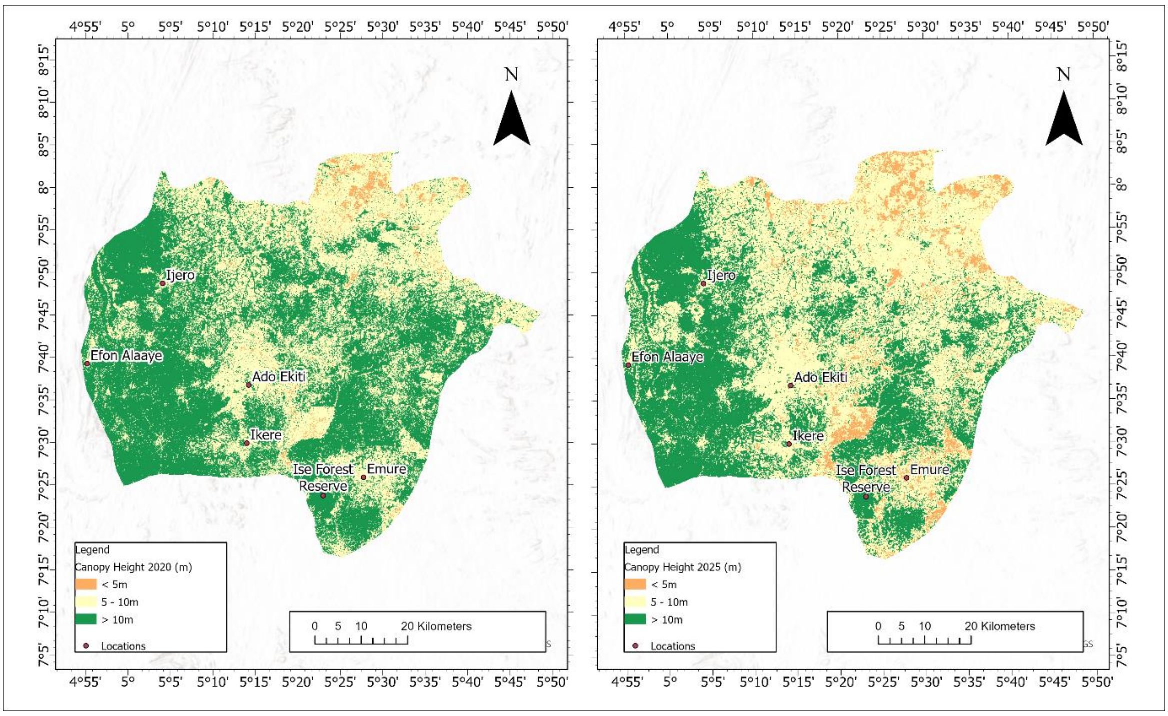

Fig. 7**: Spatiotemporal Evolution of Canopy Height in Ekiti State (2020–2025)**

Spaceborne LiDAR data from the Global Ecosystem Dynamics Investigation were used to derive canopy height metrics for Ekiti State in 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 ± 3.42 m. In 2025, canopy height ranged from 2.35 m to 27.89 m, with a mean value of 9.34 ± 3.48 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.

4.7. Comparison with the UMD/GLAD 2020 Forest Height Product

To provide an independent assessment of our GEDI-calibrated canopy height model, the predicted canopy height (CHM_2020) was compared with the University of Maryland (UMD) global 30-m forest canopy height product (Potapov et al., 2021). The comparison revealed a strong positive correlation between the two datasets (Pearson's $r = 0.705$, $p < 0.001$), with the UMD product explaining approximately 50% of the variance in our CHM ($R^2 = 0.497$). The comparison metrics (Table 5) yielded an RMSE of 4.78 m, an MAE of 3.84 m, and a mean bias of +2.83 m, indicating that our locally calibrated CHM estimated taller canopy heights than the UMD product on average.

Table 5: Comparison of GEDI-calibrated CHM (2020) with UMD/GLAD 2020 forest height product (Potapov et al., 2021) for Ekiti State.

Metric	RF CHM vs UMD Forest Height
Pearson's r	0.705
R^2	0.497
RMSE (m)	4.78
MAE (m)	3.84
Bias (m)	2.83

4.8. 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 6). At the 5 m threshold, F1-scores were 0.573 (2020) and 0.459 (2025), with recall values of 0.421 and 0.370, respectively. At the 10 m threshold, F1-scores were 0.748 (2020) and 0.695 (2025), with recall values of 0.650 and 0.587, respectively (Table 6).

Overall accuracy was relatively above ~77% at the 10 m threshold, while the overall accuracy of the 5 m threshold was below 42%.

Table 6. 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	0.401	0.573	0.421
2020	10	0.879	0.650	0.748	0.770
2025	5	0.998	0.298	0.459	0.370
2025	10	0.853	0.587	0.695	0.800

5. Discussion

This study integrated multi-sensor SAR, optical, and GEDI LiDAR datasets to develop a threshold-based assessment for evaluating Spectral–Structural Divergence in Forest Extent under Land-Use Change in Ekiti State, Nigeria. The results reveal substantial forest decline alongside progressive reductions in canopy structural condition and demonstrate limitations in the ability of spectral classifications to represent structurally defined forest extent fully.

5.1. Multi-sensor LULC classification performance

Although the top predictors of LULC classification are the optical sensors and their respective indices, which contribute 69.85%, 62.21%, and 59.49% of the total predictors in the 2007, 2015 and 2025 epochs, respectively, the structural sensors consistently recorded 19.24%, 28.81%, and 29.11%, which highlight the contribution of structural variables in distinguishing land use/land cover classes. The terrain predictors recorded 10.91%, 8.97%, and 11.40% for the three epochs, indicating that topographic conditions also influenced class discrimination across the heterogeneous landscape of Ekiti State. These findings support previous studies showing that integrating optical, SAR, and terrain information improves LULC classification in tropical environments (Prudente et al., 2022; Sarker et al.,2026).

The random forest classifiers achieved accuracies of 72.48%, 75.93%, and 82.35%, with corresponding Kappa coefficients of 0.662, 0.70, and 0.753, respectively, across 2007, 2015 and 2025 epochs. The accuracies and kappa coefficient demonstrate progressive improvement and provide confidence in the suitability for the LULC classification and spectral-structural assessment.

The producer accuracy and user accuracy at the class level show that built-up and water and rock outcrops classes exhibited higher producer accuracy, while agriculture exhibited moderate producer and user accuracy across the three epochs.

There is observable low accuracy recorded for shrubland in all the epochs (PA = 46.48–57.35%; UA = 50.65–51.61%). The low accuracy observed for shrubland is consistent with findings from other tropical landscapes, where shrubland classification is limited by spectral similarity with regenerating agriculture and phenological noise, particularly when shrub coverage falls below 60% (Liu et al.,2026).

The forest class maintained consistent producer's accuracies (77–83%) across all epochs, comparable to accuracies reported in other tropical forest mapping studies. The improvement in overall accuracy from 72.48% in 2007 to 82.35% in 2025 reflects the value of multi-sensor fusion, combining optical, SAR, and terrain data, which has been shown to enhance class separability in tropical environments where cloud cover and landscape heterogeneity present significant challenges.

5.2. Land-use/land-cover and forest-extent change, 2007–2025

The land use/landcover changes in Ekiti State from 2007 to 2025 show a significant expansion of built-up areas from 167.86 km^2 in 2007 to 621.63 km^2 in 2025, representing an overall increase of 270.33%. In contrast, the forest declined from 2193.19 km^2 to 1469.19 km^2 in 2025, which marked an approximate 33% reduction in the area covered by forest and its conversion to other land uses. These findings are consistent with previous investigations that documented substantial forest reduction and increasing ecological disturbance driven by agricultural expansion and urban growth (Festus, 2012; Olorunfemi et al., 2020) across the region. The present study extends these findings by incorporating GEDI-derived structural information, demonstrating that forest degradation in Ekiti State involves not only areal forest loss but also reductions in vertical forest structure within remaining vegetation patches.

Moreover, the loss of approximately 724km^2 of forest over the 18-year study period represents an average annual forest loss of approximately 40.4 km^2 yr^{-1} in Ekiti State. This persistent decline is consistent with Nigeria's Revised Forest Reference Emission Level (FREL), which identified ongoing deforestation across the country's ecological zones, with an estimated annual deforestation rate of 335,811 ha year^{-1} between 2017 and 2021 (Federal Ministry of Environment & Federal Department of Forestry, 2026). Notably, Ekiti State lies within the lowland forest–Guinea savanna transition zone, where the FREL identifies some of the highest levels of deforestation in the country. This suggests that the forest decline observed in Ekiti State reflects broader patterns of forest loss occurring across Nigeria.

5.3. Predictor importance in GEDI-derived canopy-height modelling

The recursive feature elimination result indicates that the optical predictors (NDMI, NDVI, NBR, SWIR bands (B11 and B12) were the dominant predictors of the canopy height model in 2020 and 2025. The optical predictors accounted for 37% and 50% respectively in the two epochs. This highlights the dominance of spectral information relating to vegetation greenness, moisture status, forest disturbance, and canopy condition in explaining canopy height variability. The dominance of optical predictors observed in this study is consistent with the findings of Ngo et al. (2023), who reported that optical Sentinel-2 variables were the most informative predictors of GEDI-derived canopy height among 77 remotely sensed features evaluated across tropical forests in South America and Africa.

Although the optical sensors contributed the greatest importance to predictors of canopy height, the synthetic aperture radar predictors also made significant and substantial contributions in the two epochs (31.0% and 35.6%). This reflects the ability of microwave backscatter to penetrate vegetation canopies and capture structural attributes that are not directly observable from optical reflectance alone.

Terrain variables accounted for only 10.0% and 9.3%, indicating that topographic effects played a comparatively smaller role in explaining canopy-height variability across the study area. The contribution of derived interaction variables further demonstrates that combining spectral, structural, and topographic information improves the representation of forest structure compared with any individual data source.

5.4. GEDI-derived canopy-height model performance and structural change

The Random Forest canopy-height model achieved moderate predictive performance, with R^2 values of 0.35 and 0.41, RMSE of 4.46 m and 4.43 m, and MAE values of 3.43 m and 3.44 m for 2020 and 2025, respectively.

The moderate predictive performance of the model was a challenging aspect of modelling canopy height and forest structure in tropical forests using GEDI data. This could be attributed to several factors, including the sparse and limited GEDI observations, which make it difficult to model the complex heterogeneity of tropical landscapes, resulting in some forest structural conditions being under-represented. Ngo et al. (2023) similarly highlighted that the sparse spatial distribution of GEDI footprints requires extrapolation using remotely sensed predictors to generate continuous canopy height surfaces. Moreover, optical predictors are prone to signal saturation in dense tropical forests, thereby reducing their sensitivity to variations in canopy height beyond certain structural thresholds.

Despite extensive model optimisation, including hyperparameter tuning and logarithmic transformation of the response variable, only marginal improvements in predictive performance were achieved, suggesting that model performance had reached a practical plateau. This indicates that the remaining unexplained variance is more likely associated with limitations in the available predictor variables and the inherent complexity of tropical forest structure than with model parameterisation.

Other factors contributing to the moderate predictive performance may be the inherent complexity of tropical rainforest ecosystems, which cannot be fully explained using satellite-derived predictors alone. Factors such as species composition, forest stand age and structure, soil and edaphic conditions, climate variability, and understory composition were not represented in the predictor stack but are likely to influence canopy height variability and, consequently, the predictive performance of the model.

The comparison of the GEDI calibrated canopy height model and UMD/GLAD 2020 forest product revealed a strong positive correlation ($r=0.705$, $R^2 = 0.497$), indicating that the locally calibrated model successfully captured the broad spatial pattern of canopy height in Ekiti State. The RMSE (4.78 m), MAE (3.84 m), and positive bias (2.83 m) indicate reasonable agreement between the two canopy height products. The positive bias of 2.83 indicated that the locally calibrated CHM was higher. This difference reflects the local calibration of the GEDI-calibrated CHM, whereas the UMD product is globally calibrated for application across diverse forest ecosystems (Potapov et al.,2021).

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 (a reduction of 1.26 m). While this decline is within the model error (RMSE = 4.46 m), the consistent spatial pattern suggests progressive structural degradation at the landscape scale rather than precise pixel-level canopy height change.

5.5. Threshold-dependent spectral–structural divergence (≥5 m and ≥10 m)

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

Validation results showed low recall at the 5 m canopy height threshold, indicating that a substantial proportion of the forest meeting this threshold was omitted from spectral classifications. The low performance at the 5m threshold is particularly concerning, given that this is the FAO minimum criterion for forest definition (FAO, 2018). This suggests that the spectral classifications may underestimate forest extent in landscapes undergoing land use changes.

There is improved agreement at the 10 m threshold, suggesting that spectrally derived forest extent more reliably captures mature forest stands than low-stature or regenerating vegetation. These findings suggest that spectral classifications may not fully represent vertical forest structure. Consequently, the observed divergence necessitates incorporating GEDI-LiDAR-derived structural information, in addition to conventional land cover products, for monitoring global forest characterisation and canopy height (Potapov et al., 2021).

6. Conclusion

This study demonstrates the value of integrating SAR, optical, and GEDI LiDAR datasets for evaluating forest change and urban expansion in tropical landscapes. While horizontal forest loss in Ekiti State reached 33.03% between 2007 and 2025, structural analysis further revealed reductions in canopy height and forest structural condition within remaining vegetation areas. The results indicate that spectrally derived forest classifications may not fully capture the underlying structural dynamics of forests, particularly in rapidly changing land use landscapes.

The study further revealed that urban expansion and agricultural activities were the major drivers of both forest conversion and structural degradation in Ekiti State. The divergence observed between spectrally mapped forest extent and structurally defined forest condition indicates that the persistence of forest cover does not necessarily imply the maintenance of forest structural integrity. This demonstrates the importance of integrating GEDI-derived structural metrics with optical and SAR datasets to provide a more comprehensive assessment of forest condition than spectral information alone.

The study proposes a spectral–structural assessment framework as a practical approach for improving forest monitoring, forest degradation assessment, and land-use planning in tropical landscapes. The integration of forest structural information into routine forest monitoring can support sustainable forest management, biodiversity conservation, carbon accounting, and climate change mitigation.

6.1. Limitations of the study.

The study developed a spectral-structural assessment framework to evaluate the agreement between LULC-derived forest extent and GEDI-informed canopy height model forest extent in landscapes undergoing land-use change. Although the proposed framework provides a practical approach for integrating spectral and structural information for forest monitoring, several methodological limitations should be acknowledged.

First, the canopy-height model performance reported for the study indicated moderate R^2 values of 0.35 (2020) and 0.41 (2025). This reflects the complexities of tropical rainforest. Consequently, the canopy height model should be interpreted as a structural proxy for structural assessment rather than engineering-grade height estimation.

Second, GEDI LiDAR provides sparse data and a discrete sampling footprint, rather than continuous wall-to-wall observations. A random forest was used to extrapolate the quality-filtered GEDI observations into a continuous wall-to-wall canopy height surface. Some local structural variability may not have been fully represented, particularly in areas with limited footprint coverage.

Third, the integration of Landsat, Sentinel-1, Sentinel-2, ALOS PALSAR, and SRTM datasets required harmonisation of data acquired at different spatial resolutions and acquisition dates. While preprocessing procedures were applied to ensure spatial consistency, differences among sensors may have introduced additional uncertainty into the canopy-height modelling and spectral–structural comparison.

Field-based validation using Terrestrial Laser scanning (TLS) or direct field inventory measurement was not available. Consequently, the predicted canopy height model was evaluated against the independent UMD/GLAD canopy-height product rather than in-situ measurement. Future studies integrating field observations or terrestrial LiDAR data would provide a more rigorous assessment of canopy-height accuracy and further strengthen the proposed framework.

Finally, areal uncertainty was not explicitly quantified; therefore, land-cover area estimates should be interpreted alongside the reported classification accuracies.

Declarations

Funding

The authors received no specific funding for this work.

Competing Interests

The authors declare no competing interests.

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request. Remote sensing datasets used in this study are publicly available through Google Earth Engine and associated satellite data repositories, including Landsat, Sentinel, MODIS, GEDI, ALOS PALSAR, and SRTM databases.

Ethical Responsibilities

All authors have read, understood, and complied with the ethical responsibilities of authors as stated in the journal guidelines.

Preprint Availability

An earlier preprint version of this study is publicly available on EarthArXiv (Bejide et al., 2026).

REFERENCES

1. Adegboyega, E. R., & Adebayo, W. O. (2018). *Geospatial information for sustainable forest management in Ekiti State*. In *FIG Congress Proceedings*.
2. Adeoye, N. O., & Ayeni, B. (2011). Assessment of deforestation, biodiversity loss and the associated factors: case study of Ijesa-Ekiti region of Southwestern Nigeria. *GeoJournal*, *76*(3), 229-243.
3. Bejide, O. D., Emiola, K. D., Ajewole, O. D., & Olaniran, H. D. (2026). Urbanisation-driven spectral–structural divergence in forest extent: Threshold-based validation using GEDI LiDAR in Ekiti State, Nigeria. *EarthArXiv*. https://doi.org/10.31223/X5FZ03
4. Bossy T, Ciais P, Renaudineau S, Wan L, Ygorra B, Adam E, Barbier N, Bauters M, Delbart N, Frappart F, Gara TW, Hamunyela E, Ifo SA, Jaffrain G, Maisongrande P, Mugabowindekwe M, Mugiraneza T, Normandin C, Obame CV, Peaucelle M, Pinet C, Ploton P, Sagang LB, Schwartz M, Sollier V, Sonké B, Tresson P, De Truchis A, Vo Quang A and Wigneron J-P (2025) State of the art in remote sensing monitoring of carbon dynamics in African tropical forests. Front. Remote Sens. 6:1532280. https://doi.org/10.3389/frsen.2025.1532280

5. Cho, M. S., Roy, D. P., Kashongwe, H. B., Yan, L., & Shen, M. (2025). Assessment and improvement of GEDI canopy height estimation in tropical and temperate forests. *Science of Remote Sensing*, *11*, Article 100221. https://doi.org/10.1016/j.srs.2025.100221
6. Fasona, M. J., Akintuyi, A. O., Adeonipekun, P. A., Akoso, T. M., Udofia, S. K., Agboola, O. O., Ogunsanwo, G. E., Ariori, A. N., Omojola, A. S., Soneye, A. S., & Ogundipe, O. T. (2022). Recent trends in land-use and cover change and deforestation in south-west Nigeria. *GeoJournal*, 87(3), 1411–1437. https://doi.org/10.1007/s10708-020-10318-w
7. Fayad, I., Baghdadi, N. N., Alcarde Alvares, C., Stape, J. L., Bailly, J. S., Scolforo, H. F., Zribi, M., & Le Maire, G. (2021). Assessment of GEDI's LiDAR data for the estimation of canopy heights and wood volume of eucalyptus plantations in Brazil. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 7095–7110. https://doi.org/10.1109/JSTARS.2021.3092836
8. Federal Ministry of Environment, Federal Department of Forestry. (2026). Revised National Forest Reference Emission Level (FREL) for the Federal Republic of Nigeria. United Nations Framework Convention on Climate Change (UNFCCC). https://redd.unfccc.int/media/nigeria_frel_submission.pdf
9. Festus, I. A. (2012). Appraisal of the causes and consequences of human-induced deforestation in Ekiti State, Nigeria. *Journal of Sustainable Development in Africa, 14*(3), 37–52.
10. Food and Agriculture Organization of the United Nations. (2018). Global forest resources assessment - FRA 2020: Terms and definitions (Working Paper No. 188). https://openknowledge.fao.org/items/9ed642d3-c6f7-459b-bcb8-1af25cfbbec6
11. Gao, Y., Skutsch, M., Paneque-Gálvez, J., & Ghilardi, A. (2020). Remote sensing of forest degradation: A review. *Environmental Research Letters*, *15*(10), Article 103001. https://doi.org/10.1088/1748-9326/abaad7
12. Güneralp, B., Lwasa, S., Masundire, H., Parnell, S., & Seto, K. C. (2017). Urbanization in Africa: Challenges and opportunities for conservation. *Environmental Research Letters*, 13(1), Article 015002. https://doi.org/10.1088/1748-9326/aa94fe
13. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693
14. Hosseiny, B., Zaboli, M., & Homayouni, S. (2024). Forest change mapping using multi-source satellite SAR, optical, and LiDAR remote sensing data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 10, 163-168. https://doi.org/10.5194/isprs-annals-X-4-2024-163-2024
15. Liu, L., Zhang, Y., Zheng, Z., Zhao, G., Cong, N., & Liu, H. (2026). Underestimated shrubland distribution in the Eurasian drylands. International Journal of Applied Earth Observation and Geoinformation, 146, 105144.
16. Mbow, C., Brandt, M., Ouedraogo, I., de Leeuw, J., & Marshall, M. (2015). What four decades of Earth observation tell us about land degradation in the Sahel? *Remote Sensing*, 7(4), 4048–4067. https://doi.org/10.3390/rs70404048
17. Mullissa, A., Saatchi, S., Dalagnol, R., Erickson, T., Provost, N., Osborn, F., ... Melling, D. (2024). LUCA: A Sentinel-1 SAR-based global forest land use change alert. *Remote Sensing*, *16*, Article 2151. https://doi.org/10.3390/rs16122151

18. National Population Commission. (2022). *Report on the state of the Nigerian population 2022: Population dynamics and sustainable development in Nigeria*. https://nationalpopulation.gov.ng

19. Ngo, Y.-N., Ho Tong Minh, D., Baghdadi, N., & Fayad, I. (2023). Tropical forest top height by GEDI: From sparse coverage to continuous data. Remote Sensing, 15(4), 975. https://doi.org/10.3390/rs15040975

20. Olorunfemi, I.E., Fasinmirin, J.T., Olufayo, A.A. *et al.* GIS and remote sensing-based analysis of the impacts of land use/land cover change (LULCC) on the environmental sustainability of Ekiti State, southwestern Nigeria. *Environ Dev Sustain* 22, 661–692 (2020). https://doi.org/10.1007/s10668-018-0214-z

21. Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., Pickens, A., Turubanova, S., Tang, H., Silva, C. E., Armston, J., Dubayah, R., Blair, J. B., & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment, 253*, Article 112165. http://doi.org/10.1016/j.rse.2020.112165

22. Prudente, V. H. R., Skakun, S., Oldoni, L. V., Xaud, H. A., Xaud, M. R., Adami, M., & Sanches, I. D. A. (2022). Multisensor approach to land use and land cover mapping in Brazilian Amazon. *ISPRS Journal of Photogrammetry and Remote Sensing*, *189*, 95-109.

23. Sarker, S., Chowdhury, M. A., Wang, X., & Azad, A. (2026). Cross evaluation of optical versus Sentinel-1 and 2 fusion data for tropical ecosystem mapping. Discover Geoscience, 4(1), 134. https://doi.org/10.1007/s44288-026-00512-7