Structural–carbon decoupling and forest structural thinning in degrading forests of Southwestern Nigeria using GEDI LiDAR and multi-sensor data fusion

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Abstract:

Accurate monitoring of forest degradation requires indicators that capture both structural condition and carbon dynamics. While canopy height derived from spaceborne LiDAR is widely used as a proxy for forest condition, its ability to represent aboveground biomass (AGB) under ongoing degradation remains uncertain. This study examines the relationship between canopy height and AGB in tropical forests of Southwestern Nigeria between 2020 and 2025 using GEDI LiDAR and multi-sensor data.

Canopy height (RH98) and AGB were modelled independently using machine learning and multi-source predictors. Model performance was moderate ($R^2 = 0.38$–0.49 for canopy height; $R^2 = 0.45$–0.48 for AGB). Both variables declined over time; however, biomass loss (20–39%) consistently exceeded canopy height reduction (10–23%).

A structural–carbon decoupling index (DI = 1.83) indicates that biomass declined approximately 1.8 times faster than canopy height. Aboveground carbon decreased from 111.6 to 77.7 tCO_2 ha^{-1}, corresponding to a loss of ~33.9 tCO_2 ha^{-1}. Spatial patterns indicate structural thinning rather than complete canopy loss.

These findings demonstrate that canopy height alone may underestimate carbon loss in degrading tropical forests and highlight the importance of integrating multi-sensor data for large-scale forest monitoring.

Keywords: Forest degradation, Canopy Height Model (CHM), Multi-sensor data fusion, Carbon storage, Machine learning, Sub-Sahara Africa.

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1.0 Introduction

Forest ecosystems play a central role in carbon cycling, biodiversity maintenance, and climate regulation by storing large amounts of carbon in living biomass and soils (IPCC, 2021; Harris et al., 2021). In tropical regions, however, increasing deforestation, land conversion, and other anthropogenic pressures are reducing forest structural integrity and weakening carbon storage capacity. While deforestation is readily detectable, more subtle forms of degradation where forest structure is altered without complete canopy removal remain difficult to quantify using conventional approaches.

Understanding forest degradation requires more than mapping vegetation cover alone. Key structural attributes such as canopy height, vegetation density, and vertical complexity strongly influence biomass accumulation, biodiversity, and ecosystem resilience (LaRue et al., 2023; de Conto et al., 2024; Liu et al., 2024; Sun et al., 2025). Aboveground biomass (AGB) is particularly important because it provides a direct basis for estimating carbon stocks and assessing the climate relevance of forest change (Crockett et al., 2023; Sun et al., 2025). However, conventional field-based methods for estimating biomass and forest structure are labour-intensive, costly, and difficult to scale across large, heterogeneous tropical landscapes (Finger et al., 2025; Kemigyisha et al., 2025; Papucci et al., 2026).

Satellite remote sensing has significantly improved the capacity for wall-to-wall monitoring of forest dynamics across broad spatial extents (Goetz et al., 2009; Francini et al., 2024). Yet many conventional optical approaches remain limited because greenness-based indices often saturate in dense vegetation and are insufficiently sensitive to three-dimensional structural degradation. The Global Ecosystem Dynamics Investigation (GEDI) mission provides an important advance by directly measuring vertical forest structure through spaceborne LiDAR, enabling improved estimation of canopy height, relative height metrics, and structural variability (Dubayah et al., 2020). When integrated with optical and radar data, GEDI offers a strong basis for regional modelling of forest structure and biomass, particularly in tropical environments where persistent cloud cover limits optical observations (Shendryk, 2022; Ngo et al., 2023; Tsao et al., 2023).

Previous studies have demonstrated the value of GEDI and multi-sensor fusion for canopy height and biomass estimation across tropical systems, including in Nigeria (Tsao et al., 2023; Holcomb et al., 2024; Duncanson et al., 2026; Subedi et al., 2026; Bejide et al., 2026). However, most approaches either derive biomass directly from canopy height or treat structural and biomass metrics independently, limiting insight into their coupled behaviour under degradation. This is particularly important because canopy height is often implicitly assumed to represent biomass and carbon storage, despite the possibility that reductions in stem density, wood volume, and sub-canopy structure may occur without proportional changes in canopy height.

Despite advances in LiDAR-based forest monitoring, it remains unclear whether canopy height reliably represents biomass dynamics under progressive forest degradation. This uncertainty limits the ability of current Earth observation frameworks to accurately quantify carbon loss in disturbed tropical systems.

This study addresses this gap by providing a multi-temporal assessment of canopy height and aboveground biomass across a tropical forest system in Southwestern Nigeria for 2020 and 2025 using GEDI LiDAR and multi-sensor data fusion. Unlike conventional approaches that derive biomass directly from predicted height, this study models canopy height and biomass as independent outputs from GEDI, enabling a direct evaluation of structural–carbon dynamics. The modelling framework further prioritises biophysical predictors by excluding categorical variables such as land use/land cover (LULC) and spatial coordinates, thereby improving interpretability and generalisation.

The study aims to (i) model canopy height and aboveground biomass, (ii) quantify their spatiotemporal dynamics, and (iii) examine the relationship between structural and biomass changes in order to assess forest degradation patterns and identify potential decoupling between forest structure and carbon storage.

This study contributes to forest monitoring by explicitly quantifying structural–carbon decoupling using independently modelled LiDAR-derived canopy height and biomass. By introducing a decoupling index and evaluating its spatial and temporal patterns, the study provides a framework for detecting hidden biomass loss in forests that retain apparent structural integrity.

2.0 Materials and Methods

2.1 Study Area

Southwestern Nigeria (6°21′–8°10′N, 2°40′–6°00′E) comprises Ekiti, Ondo, Osun, Oyo, Ogun, and Lagos States and forms part of the Guinea–Congo rainforest belt, one of the most ecologically significant zones in West Africa (Adegboyega & Adebayo, 2018; Enaruvbe et al., 2021). The region is bounded by the Republic of Bénin to the west and the Bight of Benin to the south. Rapid urban expansion in major cities such as Lagos, Ibadan, Akure, Ado-Ekiti, and Abeokuta has intensified anthropogenic pressure on surrounding forest landscapes (Adeleke et al., 2020).

The climate is humid tropical, with a distinct bimodal rainfall regime ranging from approximately 1,500 to 2,500 mm annually and mean temperatures between 26 °C and 28 °C (Adegboyega & Adebayo, 2018). Vegetation is dominated by lowland tropical rainforest in the south, transitioning to derived savanna toward the north, reflecting both climatic gradients and long-term human disturbance (Enaruvbe et al., 2021; Fasona et al., 2022).

Land use is characterised by a mosaic of agriculture, agroforestry, plantation systems, and expanding urban areas. Major crops include cocoa, oil palm, rubber, cassava, and maize, while logging, plantation expansion, and urbanisation have led to extensive forest fragmentation and degradation (Adeleke et al., 2020; Akinde et al., 2020; Enaruvbe et al., 2021). These combined climatic and anthropogenic pressures make the region a suitable system for evaluating forest structural dynamics, aboveground biomass change, and carbon-related ecosystem decline using multi-sensor remote sensing approaches.

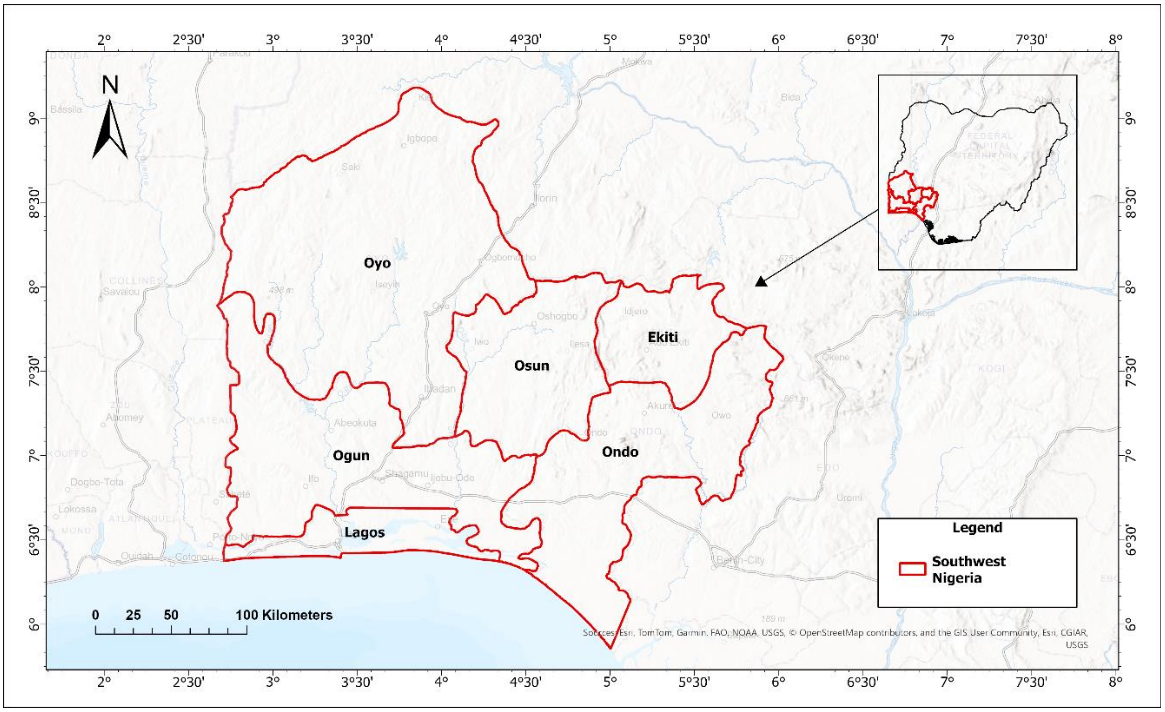

Figure 1: Map of Southwest Nigeria.

2.2 Data Sources

This study integrates multi-sensor remote sensing datasets, including GEDI LiDAR, Sentinel-1 SAR, Sentinel-2 optical imagery, ALOS PALSAR, SRTM DEM, TerraClimate, and soil data. GEDI-derived relative height (RH98) and aboveground biomass density (AGBD) were used as independent target variables to avoid circularity between canopy height and biomass estimation. Coarse-resolution environmental datasets (e.g., TerraClimate ~4 km) were resampled to match finer-resolution inputs and are interpreted as large-scale environmental constraints rather than fine-scale drivers.

2.3 Data Processing and Extraction

GEDI LiDAR observations (RH98 and AGBD) were extracted and integrated with multi-source predictor variables using a cloud-based geospatial workflow. Predictor variables were sampled at GEDI footprint locations to generate a dataset linking structural metrics with spectral, radar, topographic, and environmental features. The resulting dataset was used for subsequent machine learning modelling.

2.4 Predictor Variables

Table 1: Predictor variables used for modelling canopy height and Aboveground Biomass

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/HV, HH-HV, RVI, GLCM texture metrics)	Sentinel-1 PALSAR	Canopy density, and structural complexity
Terrain	Elevation, Slope, TWI	SRTM DEM	Topographic controls vegetation distribution
Climate	Precipitation, vapour density deficit (VPD), actual and potential evapotranspiration (AET & PET).	Terraclimate	Environmental constraints on growth
Soil	Soil Clay, Sand, PH, Bulk density, SOC	SoilGrids/OpenLandMap	Edaphic control on biomass and production

The modelling framework was designed to predict two target variables:

(i) Canopy Height Model (CHM) derived from GEDI relative height metric (RH98), and

(ii) Aboveground Biomass Density (AGBD) derived from GEDI LiDAR observations.

2.5 Model Development

Canopy height (RH98) and aboveground biomass density (AGBD) were modelled independently using Random Forest (RF) and Extreme Gradient Boosting (XGBoost) algorithms to capture non-linear relationships in high-dimensional data.

To ensure comparability between 2020 and 2025, identical predictor configurations and modelling procedures were applied across both years. The dataset was partitioned into training (80%) and testing (20%) subsets, and model performance was evaluated using R^2, RMSE, and MAE.

Categorical predictors such as land use/land cover and spatial coordinates were excluded to ensure that model outputs reflect biophysical relationships rather than spatial autocorrelation.

2.6 Decoupling Analysis

To quantify divergence between structural and carbon dynamics, a structural–carbon decoupling index (DI) was computed as the ratio of relative changes in aboveground biomass (AGB) and canopy height (CHM) between 2020 and 2025. Values >1 indicate faster biomass decline relative to canopy height. To assess robustness, percentage changes were also compared across states, allowing evaluation of whether the observed decoupling represents a consistent regional pattern.

The index is defined as

$$DI = \frac{(AGB_{2025} - AGB_{2020})/AGB_{2020}}{(CHM_{2025} - CHM_{2020})/\, CHM_{2020}}$$

Where AGB_{2025} and AGB_{2020} are mean aboveground biomass values for 2020 and 2025, respectively, and CHM_{2025} and CHM_{2020} are the corresponding mean canopy height values. Values greater than 1 indicate that biomass declined proportionally faster than canopy height.

3.0: Results

3.1 Model Performance

The canopy height (RH98) and aboveground biomass (AGBD) models demonstrated moderate predictive performance across both study years (Table 2). For canopy height, the Random Forest model achieved the highest accuracy in 2020 ($R^2 = 0.486$; RMSE = 3.39 m; MAE = 2.32 m). In 2025, model performance declined slightly, with R^2 values of 0.419 and 0.416 for Random Forest and XGBoost, respectively, although error metrics (RMSE and MAE) were marginally lower.

Aboveground biomass models exhibited comparatively lower predictive performance. Models based on structural and spectral predictors yielded R^2 values ranging from 0.395 to 0.454. The inclusion of environmental variables (soil and climate) resulted in improved model performance, with the highest accuracy observed for the XGBoost model in 2025 (R^2 = 0.475; RMSE = 25.27 t/ha; MAE = 18.25 t/ha).

Across both variables, the inclusion of environmental predictors led to an increase in model performance, while the exclusion of spatial coordinates was maintained to ensure that predictions reflect biophysical relationships rather than spatial autocorrelation.

Table 2: Model Performances

Target	Year	Model	Configuration	R^2	RMSE	MAE
CHM (RH98 m)	2020	RF	Base	0.486	3.39 m	2.32 m
CHM (RH98 m)	2025	RF	Base	0.419	2.95 m	2.23 m
CHM (RH98 m)	2025	XGB	Base	0.416	2.96 m	2.24 m
CHM (RH98 m)	2025	XGB	+ Env	0.467	3.49 m	2.26 m
AGB	2025	RF	Base	0.454	25.78 t/ha	18.73
AGB	2020	XGB	+ Env	0.435	25.01 t/ha	15.39
AGB	2025	XGB	+ Env	0.475	25.27 t/ha	18.25

3.1.1 Model Diagnostics and Residual Analysis

The diagnostic plots in Figure 2 show a clear positive relationship between observed and predicted values for both canopy height (RH98) and aboveground biomass (AGBD), indicating reasonable model performance across the dataset. For canopy height, predictions generally follow the 1:1 line, although deviations increase at higher values. Similarly, AGB predictions show good agreement with observations at low to moderate ranges, with increasing dispersion at higher biomass levels.

Residual plots indicate that errors are generally centered around zero for low to moderate predicted values. However, a clear increase in residual variance with increasing predicted values is observed, forming a funnel-shaped pattern characteristic of heteroscedasticity. This indicates that model uncertainty increases with canopy height and biomass magnitude.

In addition, both models exhibit systematic underestimation at higher values, particularly for AGB, where extreme biomass values are consistently underpredicted. This suggests a compression effect in model predictions, where high structural and biomass values are not fully captured.

Overall, the results indicate that model accuracy is highest for low to moderate values, with reduced precision and increasing uncertainty at higher canopy heights and biomass levels.

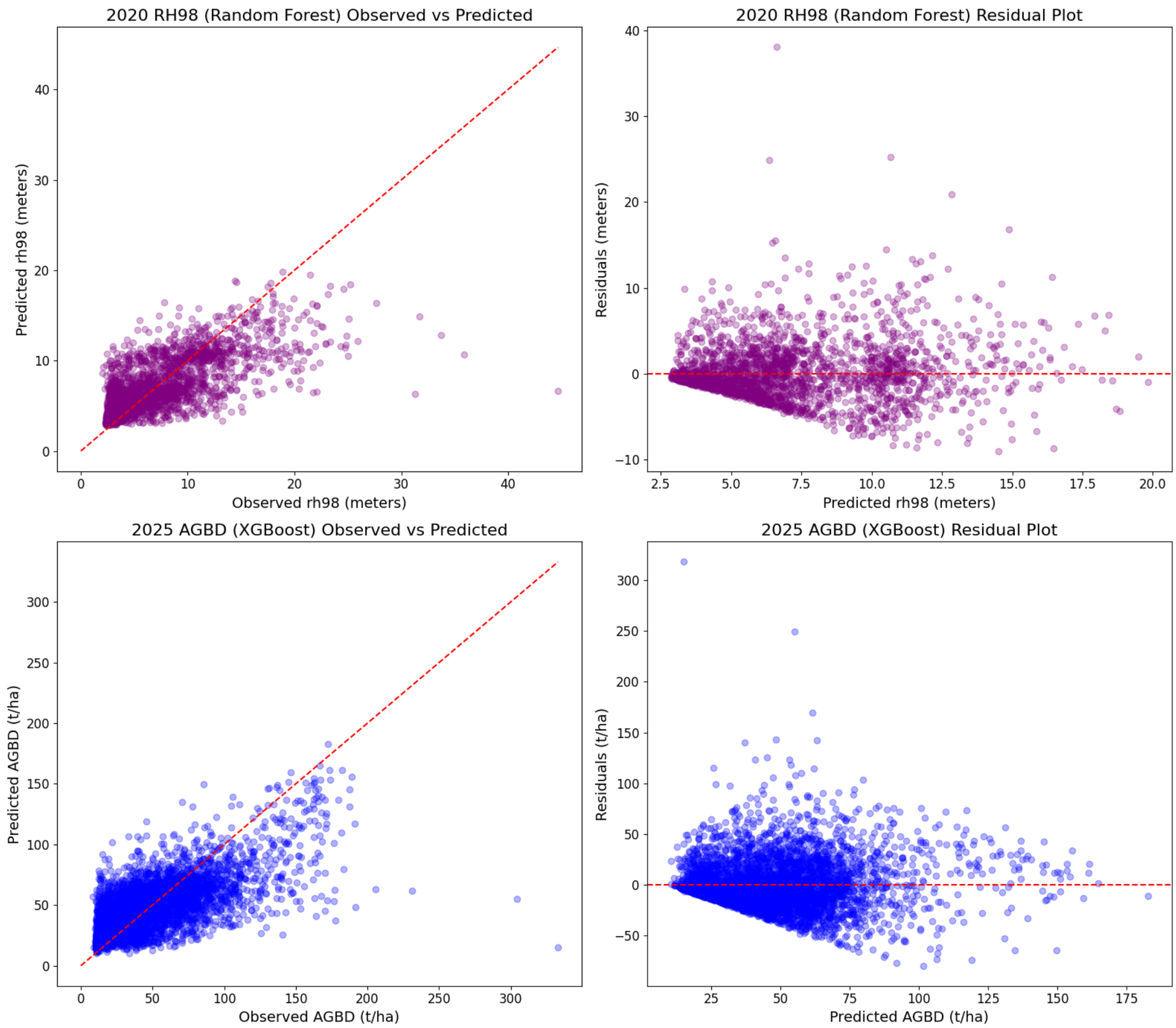

Figure 2: Model Diagnostics and Residual Analysis Plot of AGBD and CHM

3.2 Drivers of Forest Structure and Biomass

3.2.1 Feature Importance (ML)

Feature importance analysis identified the dominant predictors associated with canopy height across the study area (Figure 3). Across both years, Short-Wave Infrared (SWIR) variables and vegetation indices, including NDMI, B11, B12, and NBR, consistently ranked among the most important predictors.

In 2020, predictor importance was relatively distributed across multiple variables, with NDMI, NBR, B11, and B12 contributing the largest shares, followed by SAR backscatter (VV) and elevation. Additional contributions were observed from optical bands and SAR-derived variables, indicating a combination of spectral, structural, and topographic influences.

In contrast, the 2025 model exhibited a more concentrated importance structure, with B12 and B11 accounting for a substantially larger proportion of total importance. Other variables, including elevation, SAR backscatter, and vegetation indices, contributed comparatively smaller shares.

Overall, the results indicate a shift from a more distributed predictor influence in 2020 to a more concentrated dominance of SWIR variables in 2025. Climate and soil variables contributed minimally to canopy height predictions in both years.

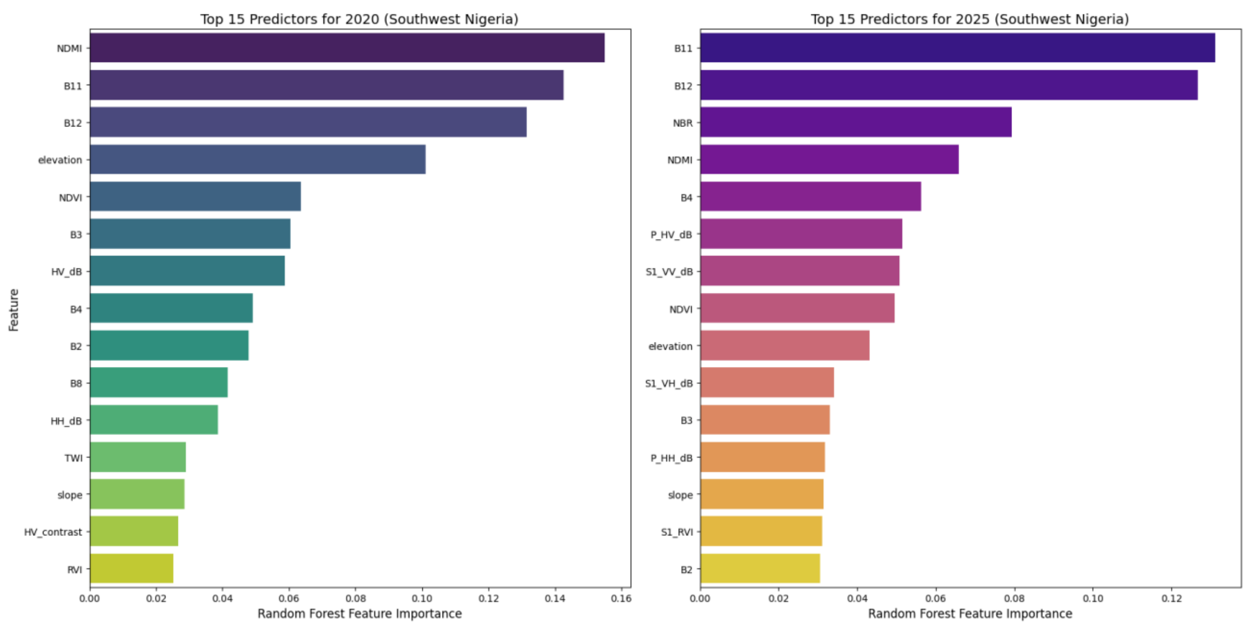

Figure 3: Predictors of canopy height in Southwest Nigeria.

The predictors of aboveground biomass are presented in Figure 4. Compared to canopy height, biomass models exhibited a more distributed pattern of predictor importance across spectral, structural, and environmental variables.

Across both years, Short-Wave Infrared (SWIR) bands, particularly B11 and B12, consistently ranked among the most important predictors. In 2020, predictor importance was strongly influenced by SWIR variables, with additional contributions from climate variables, soil properties, terrain factors, and SAR backscatter, indicating a combination of spectral and environmental influences.

In 2025, SWIR variables remained dominant, while SAR-derived metrics and disturbance-related indices contributed more prominently. Variables such as L-band SAR backscatter, SAR-based ratios, and NBR showed increased importance relative to 2020, alongside continued contributions from environmental predictors.

Overall, biomass models exhibited a broader distribution of predictor importance compared to canopy height, with contributions from spectral, SAR, topographic, and environmental variables.

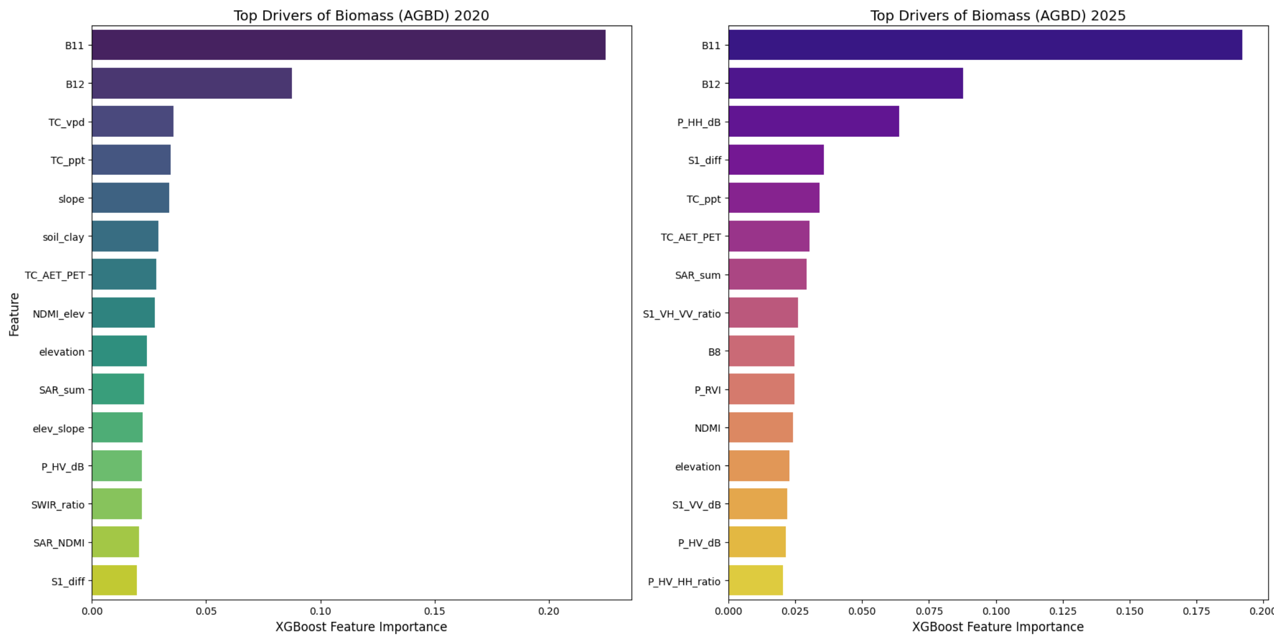

Figure 4: Predictors of aboveground biomass in Southwest Nigeria.

3.2.2 OLS Regression Analysis

To complement the machine learning results and provide statistical interpretation of predictor effects, an Ordinary Least Squares (OLS) regression analysis was conducted. The analysis was applied to both canopy height (CHM) and aboveground biomass (AGB) to quantify the direction, magnitude, and statistical significance of key predictors identified from the feature importance analysis.

3.2.2.1 Canopy Height (CHM)

An OLS regression model was fitted to canopy height (RH98) for 2025. The model showed moderate explanatory power ($R^2 = 0.343$, $p < 0.001$), indicating that a portion of the variability in canopy height is explained by the selected predictors.

Several variables were statistically significant ($p < 0.001$), including SWIR bands (B11 and B12), vegetation indices (NDMI and NBR), optical bands (B2, B3, B4), and topographic variables (slope and elevation). SAR-derived backscatter (P_HV_dB) also showed a statistically significant but smaller contribution. The results indicate that multiple spectral, structural, and topographic variables are associated with canopy height variability in the study area.

Table 4: Significant OLS Predictors of Canopy Height (2025)

Variable	Coefficient (β)	Significance
B12	119.91	p < 0.001
B11	−95.92	p < 0.001
NBR	46.7	p < 0.001
NDMI	−39.05	p < 0.001
B2	66.65	p < 0.001
B3	−73.84	p < 0.001
B4	23.08	p < 0.001
Slope	0.102	p < 0.001
Elevation	0.0017	p < 0.001
P_HV_dB	0.18	p < 0.001

3.2.2.2 Aboveground Biomass (AGB)

An Ordinary Least Squares (OLS) regression analysis was conducted to examine the statistical relationships between predictors and aboveground biomass (AGBD) for 2025. The model demonstrated moderate explanatory power ($R^2 = 0.388$, $p < 0.001$), indicating that a portion of biomass variability is explained by the selected predictors.

Several variables were statistically significant ($p < 0.001$), including SWIR bands (B11 and B12), vegetation indices (NDMI and NBR), SAR-derived metrics, environmental variables (precipitation and water balance), soil properties (clay content), and topographic variables (elevation and slope).

These results indicate that biomass variability is associated with a combination of spectral, structural, environmental, and topographic predictors across the study area.

Table 5: Significant OLS Aboveground biomass (2025)

Variable	Coefficient (β)	Significance
B12	2645.34	$p < 0.001$
B11	−1733.75	$p < 0.001$
NBR	1245.8	$p < 0.001$
NDMI	−965.25	$p < 0.001$
P_HH_dB	2.56	$p < 0.001$
P_HV_dB	−1.92	$p < 0.001$
SAR_sum	0.65	$p < 0.001$
SAR_diff	−4.48	$p < 0.001$
S1_VH_VV_ratio	−151.65	$p < 0.001$
TC_AET_PET	−199.98	$p < 0.001$
TC_ppt	0.029	$p < 0.001$
Soil_clay	−0.50	$p < 0.001$
Elevation	−0.106	$p < 0.001$
Slope	0.662	$p < 0.001$
NDMI_elev	0.258	$p < 0.001$
SAR_NDMI	6.7	$p < 0.001$

3.3 Spatiotemporal Change in Canopy Height Model (CHM)

The spatiotemporal analysis of canopy height represented in Figure 5 revealed significant changes in forest structure across Southwest Nigeria between 2020 and 2025. Overall, canopy height exhibited a consistent decline across the study area, indicating widespread structural degradation. As illustrated in Figure 5, degraded or non-forest areas (below 5 m) are represented in red, secondary canopy (5–10 m) in light green, and mature canopy (>10 m) in dark green.

In 2020, mature canopy (>10 m) formed a relatively continuous and well-developed belt across Ondo, Ekiti, and Osun States, with additional patches observed in northern Oyo, particularly around protected areas such as Old Oyo National Park. Ogun State and parts of eastern Ondo were predominantly characterized by secondary canopy (5–10 m), while northern Oyo remained largely dominated by degraded or low-canopy vegetation (<5 m).

By 2025, a marked decline in mature canopy was observed across the region. Areas previously characterized by dense canopy in Ondo, Osun, and Ekiti exhibited substantial transitions to secondary forest. Similarly, patches of mature vegetation in Ogun and Lagos showed noticeable reductions. In Oyo, particularly within Old Oyo National Park, previously intact canopy structures experienced further degradation, indicating a continued shift toward structurally simplified vegetation.

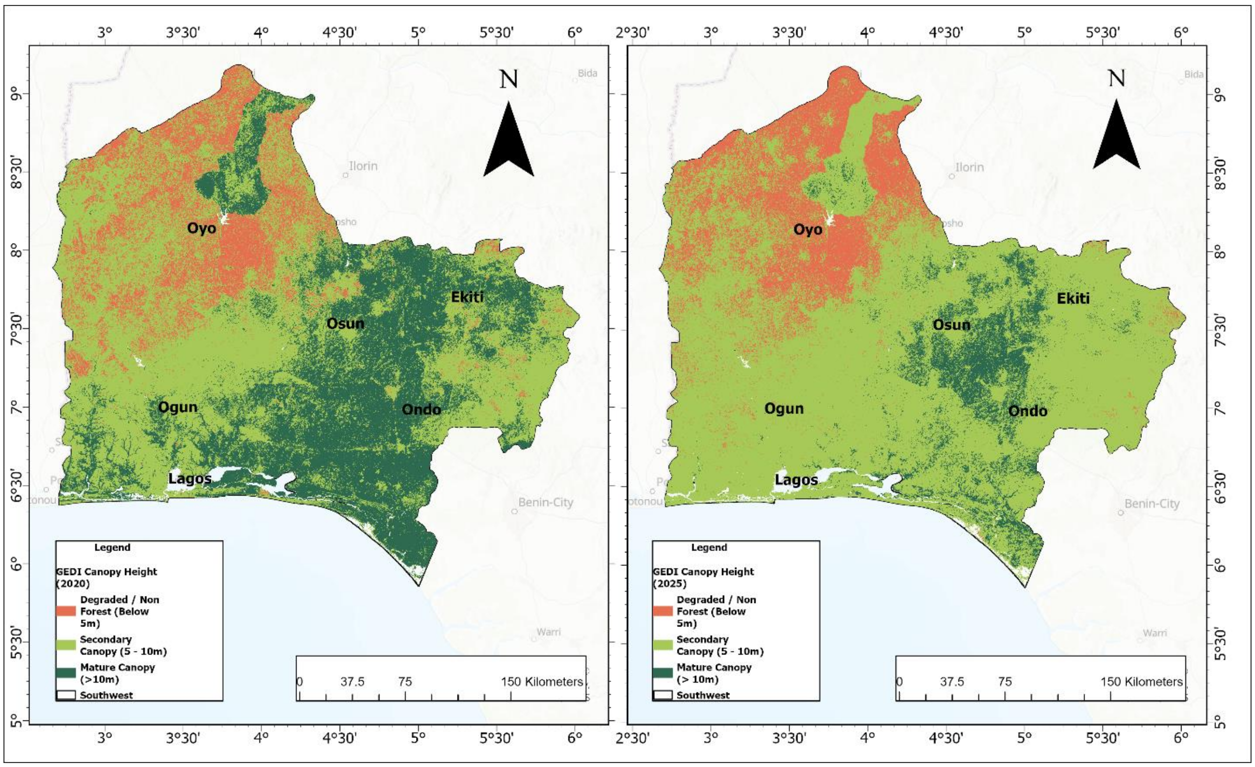

Figure 5: Change in Canopy Height from 2020 to 2025.

The average height of canopy in Southwest Nigeria in 2020 was 8.36 ± 2.97, and reduced to 6.97 ± 1.94 in 2025, representing an overall reduction of 16.63% in canopy height over the study period. All states experienced a reduction in mean canopy height over the study period, as illustrated in Table 6. Ekiti State recorded a substantial decline from 10.30 m in 2020 to 8.15 m in 2025, representing a −20.87% change. Similarly, Lagos exhibited a decrease from 9.33 m to 7.25 m (−22.20%), while Ogun showed one of the largest proportional declines, from 8.60 m to 6.63 m (−22.91%).

In Ondo and Osun, canopy height declined from 10.00 m to 8.26 m (−17.40%) and from 10.20 m to 8.82 m (−13.63%), respectively. Oyo State, which had the lowest baseline canopy height, also experienced a reduction from 6.28 m to 5.61 m, corresponding to a −10.67% change.

Overall, the results indicate a consistent pattern of canopy height reduction across all states, with the most pronounced losses observed in Ogun, Lagos, and Ekiti, highlighting widespread structural degradation

Table 6: Zonal statistics of GEDI-derived mean canopy height (rh98) across the six states of Southwest Nigeria for 2020 and 2025.

State	Average CHM (2020)	Average CHM (2025)	Change in CHM (m)	Percentage Change
Ekiti	10.30	8.15	-2.15	-20.87%
Lagos	9.33	7.25	-2.07	-22.20%
Ogun	8.60	6.63	-1.97	-22.91%
Ondo	10.00	8.26	-1.74	-17.40%
Osun	10.20	8.82	-1.39	-13.63%
Oyo	6.28	5.61	-0.67	-10.67%

3.4 Spatiotemporal Change in Above-Ground Biomass (AGB)

The spatiotemporal analysis of aboveground biomass in Figure 6 revealed substantial declines across Southwest Nigeria between 2020 and 2025. In 2020, high biomass (>100 t/ha) was concentrated in the southern region (Ondo, southern Ogun, Lagos), while moderate biomass dominated central areas and low biomass prevailed in the north (Oyo), forming a clear south–north gradient.

By 2025, high biomass areas became fragmented and reduced, with moderate and low biomass classes expanding across the region. This shift reflects widespread biomass depletion and structural degradation.

Mean AGB declined across all states (Table 7). Osun remained highest (82.55 → 57.90 t/ha), while Ogun (−38.91%), Ondo (−36.33%), and Ekiti (−32.19%) experienced the largest losses. Oyo showed the smallest decline (−20.16%). Overall, biomass losses were consistent and substantial across the region.

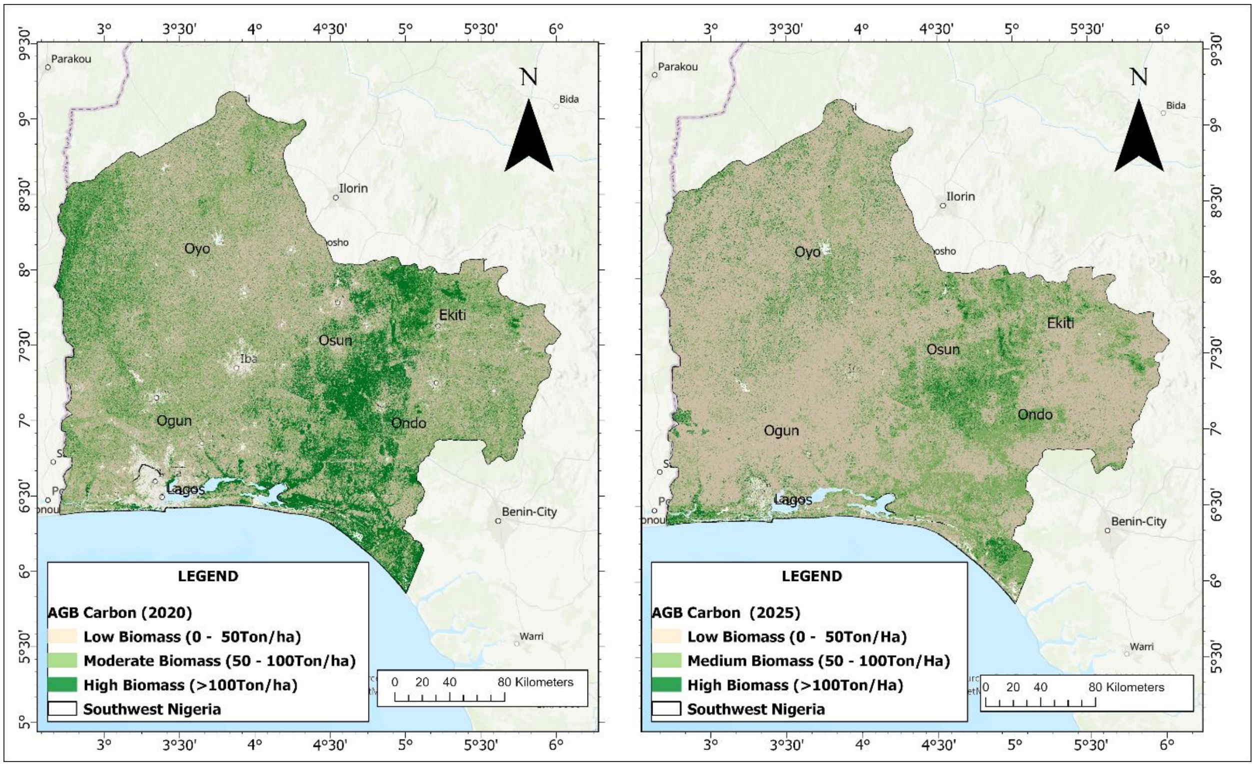

Figure 6: Change in Aboveground biomass from 2020 to 2025.

The aboveground biomass in South West Nigeria declined from 64.89 ± 44.50 t/ha in 2020 to 45.18 ± 28.34 in 2025, indicating 30.37% loss across all the states. The estimated aboveground biomass corresponds to approximately 111.61 ± 76.54 tCO_2/ha in 2020, declining to 77.71 ± 48.74 tCO_2/ha in 2025, indicating a loss of approximately 33.9 tCO_2/ha over the study period.

Table 7 represents Change in Aboveground biomass across all southwest Nigeria states from 2020 to 2025. All the states also show a decline in mean AGB between 2020 and 2025. In 2020, Osun recorded the highest mean biomass (82.55 t/ha), followed by Ondo (77.62 t/ha), Ekiti (73.64 t/ha), Lagos (71.04 t/ha), Ogun (61.81 t/ha), and Oyo (51.77 t/ha). By 2025, mean biomass values decreased across all states, with Osun still having the highest value (57.90 t/ha), followed by Lagos (54.03 t/ha), Ekiti (49.94 t/ha), Ondo (49.42 t/ha), Oyo (41.33 t/ha), and Ogun (37.76 t/ha). The high standard deviation reflects strong spatial heterogeneity across the landscape

The magnitude of decline varies by state, with Ogun showing the largest absolute reduction (−24.05 t/ha) and the highest percentage loss (−38.91%), followed by Ondo (−28.19 t/ha;

−36.33%) and Ekiti (−23.70 t/ha; −32.19%). Osun also records a substantial decline (−24.66 t/ha; −29.87%). Lagos shows a smaller but notable decrease (−17.00 t/ha; −23.94%), while Oyo exhibits the least reduction both in absolute (−10.44 t/ha) and percentage terms (−20.16%). Overall, all states experienced consistent reductions in mean AGB over the period

Table 7: State-Level Changes in Aboveground Biomass (AGB ± SD) Across Southwestern Nigeria (2020–2025)

State	Average AGB 2020 (t/ha)	Average AGB 2025 (t/ha)	Change in AGB (2020–2025)	Percentage change in AGB	Co_2 Equiv. 2020. (tCo_2/ha)	Co_2 Equiv. 2025. (tCo_2/ha)
Ogun	61.81 ± 39.09	37.76 ± 23.15	-24.05	-38.91	106.31	64.95
Ondo	77.62 ± 52.67	49.42 ± 25.31	-28.19	-36.33	133.51	85.00
Ekiti	73.64 ± 46.60	49.94 ± 24.77	-23.7	-32.19	126.66	85.90
Osun	82.55 ± 55.94	57.90 ± 32.27	-24.66	-29.87	141.99	99.59
Lagos	71.04 ± 54.57	54.03 ± 37.85	-17	-23.94	122.19	92.93
Oyo	51.77 ± 30.41	41.33 ± 28.75	-10.44	-20.16	89.04	71.09
Region	64.89 ± 44.50	45.18 ± 28.34	-19.71	-30.37%	111.61	77.71

3.5 Relationship between Canopy Height Model (CHM) and Above Ground Biomass (AGB)

Although canopy height and aboveground biomass were modelled independently, their spatial and temporal patterns show a clear correspondence across Southwestern Nigeria. Areas with higher canopy height generally coincide with higher biomass, particularly in the southern forest belt, whereas lower canopy height values are associated with lower biomass in the northern region. Intermediate canopy height classes in the central zone correspond with moderate biomass levels, indicating broad spatial agreement between vertical forest structure and carbon stock distribution.

However, the magnitude of change differs between the two variables. Between 2020 and 2025, the observed decoupling is consistent across all states, where biomass decline (−20% to −39%) exceeds canopy height reduction (−10% to −23%). This uniform pattern indicates that the divergence between structural and carbon dynamics is not localized but reflects a regional-scale response to forest degradation. While the two independently modelled surfaces remain spatially related, their temporal responses are not proportional, with AGB showing greater sensitivity to forest change than canopy height.

3.6 Structural–Biomass Decoupling Analysis

Table 8 shows that aboveground biomass declined more rapidly than canopy height between 2020 and 2025. The decoupling index (DI = 1.83) indicates that biomass declined approximately 1.8 times faster than canopy height, demonstrating a non-proportional relationship between structural and carbon dynamics.

Table 8: Structural and biomass changes with decoupling metrics (2020–2025)

Metric	2020	2025	Change (%)
Canopy height (m)	8.36	6.97	-16.63
Aboveground biomass (t/ha)	64.89	45.18	-30.37
AGB/CHM ratio	7.76	6.48	-16.49
Decoupling Index	-	-	1.83

4.0. Discussion

4.1Performance of models

The model performance for canopy height (CHM) ($R^2 = 0.486$; RMSE = 3.39 m) and aboveground biomass (AGB) ($R^2 \approx 0.47$) is consistent with values reported in large-scale remote sensing studies. For example, regional CHM models at 30 m resolution typically yield R^2 values around 0.46, despite the integration of GEDI and Sentinel data (Tamiminia et al., 2024). Similarly, AGB modelling studies have reported R^2 values ranging from 0.55 to 0.60 using Sentinel-based predictors, increasing to 0.59–0.69 when categorical variables such as forest and agro-climatic zones are included (Mohite et al., 2024).

In this study, land use/land cover (LULC) and spatial coordinates were intentionally excluded, although they improved model performance, to avoid overfitting and dominance of non-physical predictors. This likely contributed to the slightly lower R^2 but ensures that predictions are driven by biophysical relationships rather than categorical or spatial biases.

The obtained AGB performance also aligns with studies reporting R^2 values between 0.45 and 0.62 for GEDI-based regional biomass estimation (Dong et al., 2023; Castelblanco Rivera et al., 2026). Furthermore, machine learning studies often show that independent validation reduces model performance to around $R^2 \approx 0.50$, reflecting the complexity of ecological systems.

Overall, the moderate R^2 values observed in this study are expected for heterogeneous tropical landscapes.

4.2 Drivers of Structure

The feature importance results obtained in this study are consistent with previous findings on biomass and canopy structure modelling. SWIR-based variables (B11 and B12) and moisture-sensitive indices such as NDMI emerged as dominant predictors, reflecting their ability to capture canopy water content and structural characteristics. Similar observations have been reported in multi-sensor biomass studies, where SWIR bands and SAR backscatter are key drivers of AGB estimation (Mohite et al., 2024; Tamiminia et al., 2024).

The above ground biomass modelling incorporated a broader range of predictors, including climatic and soil variables, highlighting the complex controls on biomass distribution. This agrees with previous studies demonstrating that biomass is influenced not only by canopy structure but also by environmental conditions and productivity constraints (Dong et al., 2023). The stronger dependence of CHM on structural and spectral variables, compared to AGB, further reflects the more direct relationship between canopy height and remotely sensed signals.

4.3 Forest Degradation Patterns and Carbon Implications

The spatial correspondence between canopy height and aboveground biomass across Southwestern Nigeria indicates a generally positive relationship between forest vertical structure and carbon stock distribution. Areas characterized by high canopy height (>10 m) consistently align with zones of high biomass (>100 t/ha), particularly within the southern forest belt, while regions dominated by low canopy height (<5 m) correspond to low biomass classes (0–50 t/ha), especially in the northern part of the study area. This spatial alignment is observed in both 2020 and 2025, indicating that canopy height remains a key structural proxy for biomass distribution at the regional scale.

Despite this overall correspondence, the magnitude of change between 2020 and 2025 reveals a divergence in the rate of decline between CHM and AGB. Across all states, canopy height decreased by approximately 10–23%, whereas AGB declined more substantially, ranging from 20–39%. This disproportionate decline translates to a significant loss in climate regulation potential, with regional carbon storage capacity dropping from 111.61 tCO_2/ha in 2020 to 77.86 tCO_2/ha in 2025. This reduction is evident in both spatial patterns and zonal statistics, where areas transitioning from mature canopy to secondary canopy classes exhibit a sharper shift from high to moderate or low biomass. Similarly, regions with relatively modest reductions in canopy height show more pronounced decreases in biomass and associated carbon equivalents. This indicates that biomass loss is not solely a function of vertical canopy reduction but reflects broader changes in forest structure.

To further quantify this relationship, the differential rates of change suggest a weakening proportionality between canopy height and biomass over time. While CHM captures the vertical dimension of forest structure, AGB integrates additional components, including stem density, wood volume, and canopy complexity. As a result, reductions in biomass—and the subsequent release of stored carbon can occur without equivalent declines in canopy height, particularly in systems undergoing partial disturbance. The observed pattern therefore reflects a condition where forests retain moderate canopy height but exhibit reduced biomass, indicating a shift in structural composition and a diminishing carbon sequestration "ceiling" for the region.

Overall, the results demonstrate that although canopy height and biomass remain strongly associated spatially, their temporal dynamics differ, with AGB showing greater sensitivity to structural changes. This highlights the importance of integrating multiple structural and environmental indicators when assessing forest condition, as reliance on canopy height alone may not fully capture the 33.75 tCO_2/ha average loss in carbon storage detected in this study

4.4 Structural–Biomass Decoupling

The disproportionate decline in aboveground biomass relative to canopy height indicates that forest degradation in Southwestern Nigeria is characterized by structural thinning rather than complete canopy collapse. Forests retain moderate canopy height while experiencing substantial biomass loss, suggesting reductions in stem density, wood volume, and canopy complexity associated with selective logging and sub-canopy disturbance.

This pattern is quantitatively supported by the decoupling index (DI = 1.83), indicating that biomass declined approximately 1.8 times faster than canopy height between 2020 and 2025. This non-proportional relationship demonstrates a divergence between structural and carbon dynamics, highlighting a limitation of canopy height as a sole proxy for biomass. While canopy height captures vertical structure, it does not fully represent changes in forest density and carbon storage, leading to potential underestimation of degradation in disturbed tropical systems.

The consistency of this pattern across all states suggests that the observed decoupling is unlikely to be driven solely by model uncertainty. Instead, it reflects underlying ecological processes, where reductions in stem density and sub-canopy structure lead to biomass loss without proportional canopy height decline.

4.5 Limitations

Despite the robustness of the modelling framework, several limitations should be acknowledged. First, the use of coarse-resolution environmental datasets, particularly soil and climate variables (e.g., TerraClimate), introduces scale mismatches when integrated with higher-resolution optical and SAR data. Although resampling was applied, this does not create new spatial detail and may smooth local variability, potentially contributing to spatial artefacts in the biomass predictions.

Second, the reliance on GEDI LiDAR data, which provides discrete sampling rather than continuous spatial coverage, introduces uncertainty due to uneven spatial distribution of observations. This may lead to biases in areas with limited GEDI shot density, particularly when scaling to wall-to-wall predictions.

Third, the moderate model performance ($R^2 \approx 0.47$–0.48) reflects the inherent complexity of tropical forest systems, where biomass and canopy structure are influenced by multiple interacting factors, including species composition, disturbance history, and microclimatic variability that are not fully captured by remotely sensed predictors.

Additionally, the exclusion of categorical variables such as land use/land cover (LULC) and spatial coordinates (latitude and longitude), although necessary to avoid overfitting and improve model generalization, may have reduced predictive accuracy. These variables can capture important spatial and ecological patterns but risk dominating model behaviour without representing underlying biophysical processes.

While the decoupling index provides a useful metric for assessing divergence between structural and carbon dynamics, it is influenced by uncertainties in both canopy height and biomass predictions. As both variables are derived from GEDI LiDAR observations, errors in the underlying LiDAR-based estimates may propagate into the index. Consequently, the DI should be interpreted as a relative indicator of divergence rather than an exact quantitative measure of process magnitude.

Finally, the study is limited by the absence of field-based validation data, which constrains the ability to directly assess absolute accuracy of the model outputs. While GEDI provides a reliable proxy for structural measurements, uncertainties associated with LiDAR-derived biomass estimates propagate into the modelling framework.

5.0 Conclusion

This study demonstrates a significant decline in forest condition across Southwestern Nigeria between 2020 and 2025, with canopy height decreasing by 16–23% and aboveground biomass declining by up to 39%. The results show that biomass loss exceeds height reduction, indicating structural thinning and a partial decoupling between canopy height and biomass.

The findings highlight the importance of integrating multi-sensor data, particularly SWIR and SAR, for capturing forest structural changes that are not detectable using greenness indices alone. The observed reduction in carbon storage from 111.61 tCO_2/ha to 77.86 tCO_2/ha underscores a substantial loss in carbon storage capacity.

Overall, the study confirms that multi-sensor approaches provide a reliable framework for monitoring forest degradation and carbon dynamics in tropical regions, emphasizing the need for improved forest management and conservation strategies.

During the preparation of this work the author(s) used Google Gemini in order to correct the grammatical errors. 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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