Modelling Forest Structure and Aboveground Biomass Dynamics in Southwestern Nigeria Using GEDI LiDAR and Multi-Sensor Fusion

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Abstract:

This study modelled canopy height and aboveground biomass (AGB) dynamics across Southwestern Nigeria (2020–2025) by integrating GEDI LiDAR metrics with multi-sensor predictors, including optical, radar, topographic, and environmental variables. Using machine learning, the research quantified forest degradation and associated carbon loss in this data-scarce tropical region. Model performance was moderate but consistent with regional-scale studies, with Random Forest providing the best canopy height estimates in 2020 (R^2 = 0.486) and XGBoost yielding the most accurate AGB results in 2025 (R^2 = 0.475).

The findings reveal a significant ecological decline: mean canopy height decreased by 16.63% (from 8.36 m to 6.97 m), while AGB declined from 64.89 t/ha to 45.18 t/ha, representing a 30.37% reduction across the region. This reduction indicates a substantial decline in carbon storage capacity, with biomass equivalent decreasing from 111.61 tCO_2/ha in 2020 to 77.71 tCO_2/ha in 2025.

Analysis showed that canopy height is primarily driven by moisture-sensitive SWIR variables and disturbance indices, whereas AGB is influenced by a broader combination of structural, climatic, and soil factors. Notably, biomass loss consistently exceeded canopy height reduction, suggesting structural thinning, where forests lose density and carbon despite relatively stable vertical structure. These results demonstrate the effectiveness of GEDI-based multi-sensor fusion for monitoring forest degradation and carbon dynamics. The observed biomass declines highlight significant implications for carbon storage and underscore the urgent need for improved forest conservation and management strategies in Southwestern Nigeria.

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

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. In Southwestern Nigeria, where rainforest remnants are increasingly fragmented by urbanisation, agriculture, and other land-use changes, these pressures are contributing to measurable ecological decline (Festus, 2012, fasona et al.,2022).

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, especially in cloudy tropical environments where no single sensor is sufficient (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, including in Nigeria and other tropical systems (Tsao et al., 2023; Holcomb et al., 2024; Duncanson et al., 2026; Subedi et al., 2026, Bejide et al.,2026). In addition, studies from the ecological zone adjoining Southwestern Nigeria have shown that forest conversion and plantation expansion are associated with marked declines in soil fertility and carbon-related ecosystem properties, reinforcing the broader degradation signal captured from remote sensing (Enaruvbe et al., 2021).

Despite these advances, critical gaps remain. First, most studies treat canopy height and biomass independently, limiting understanding of their coupled dynamics under degradation. Second, many existing approaches rely heavily on categorical predictors such as land use/land cover (LULC) or spatial coordinates, which can artificially inflate model performance without adequately representing underlying biophysical processes. Third, regional-scale assessments in West Africa remain scarce, particularly those integrating multi-sensor data with independently derived GEDI-based structural and biomass products. As a result, the relationship between changes in vertical forest structure and biomass dynamics remains poorly understood, especially in landscapes undergoing progressive degradation rather than complete deforestation.

This study addresses these gaps by providing a regional-scale, multi-temporal assessment of canopy height and aboveground biomass across 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. This avoids the circular assumptions common in forest modelling, allowing for a genuine evaluation of how vertical structure and carbon stocks vary across different levels of degradation. In addition, the modelling framework prioritises biophysical predictors by excluding categorical variables such as LULC and spatial coordinates, thereby improving interpretability and generalisation.

This study aims to model canopy height and aboveground biomass, quantify their spatiotemporal dynamics, and examine the relationship between structural and biomass changes in order to assess forest degradation patterns.

2.0 Materials and Methods

2.1 Study Area

Southwestern Nigeria lies between latitudes 6°21′N and 8°10′N and longitudes 2°40′E and 6°00′E, covering Ekiti, Ondo, Osun, Oyo, Ogun, and Lagos state. The region forms part of the Guinea–Congo rainforest belt and represents one of the most ecologically and economically important zones in West Africa (Adegboyega & Adebayo, 2018; Enaruvbe et al., 2021). It is bounded to the west by the Republic of Bénin and to the south by the Bight of Benin along the Atlantic coastline. Major urban centres, including Lagos, Ibadan, Akure, Ado-Ekiti, Abeokuta, and Benin City, exert increasing anthropogenic pressure on the surrounding landscape (Adeleke et al., 2020).

The region is characterised by a humid tropical climate with distinct wet and dry seasons. Annual rainfall ranges from about 1,500 mm to over 2,500 mm, with a bimodal pattern peaking in June–July and September–October, while mean annual temperature varies from 26 °C to 28 °C and relative humidity is high during the wet season (Adegboyega & Adebayo, 2018). Vegetation is dominated by lowland tropical rainforest in the south, gradually transitioning into derived savanna northward, reflecting both climatic gradients and long-term human disturbance (Adegboyega & Adebayo, 2018; Enaruvbe et al., 2021).

Geologically, Southwestern Nigeria is underlain by Precambrian basement complex rocks, mainly granites, gneisses, and schists. The soils developed on these parent materials are highly weathered and are dominated by Alfisols, Ultisols, and Inceptisols, commonly corresponding to Ferric Acrisols under the WRB system. These soils are generally acidic, low to moderately fertile, and increasingly vulnerable to degradation under intensive land use (Akinde et al., 2020; Babatunde et al., 2025; Enaruvbe et al., 2021).

Land use in the region is dominated by agriculture, agroforestry, plantation systems, and rapidly expanding urban areas. Cocoa, oil palm, rubber, cassava, yam, and maize are among the major crops, while plantation expansion, logging, and urban growth have transformed large areas of the original rainforest into fragmented forests, monocultures, and mixed agroforestry systems (Adeleke et al., 2020; Akinde et al., 2020; Bejide et al., 2026; Enaruvbe et al., 2021). These interacting pressures make Southwestern Nigeria a suitable region for investigating forest structural change, aboveground biomass dynamics, and carbon-related ecosystem decline using GEDI LiDAR and multi-sensor remote sensing.

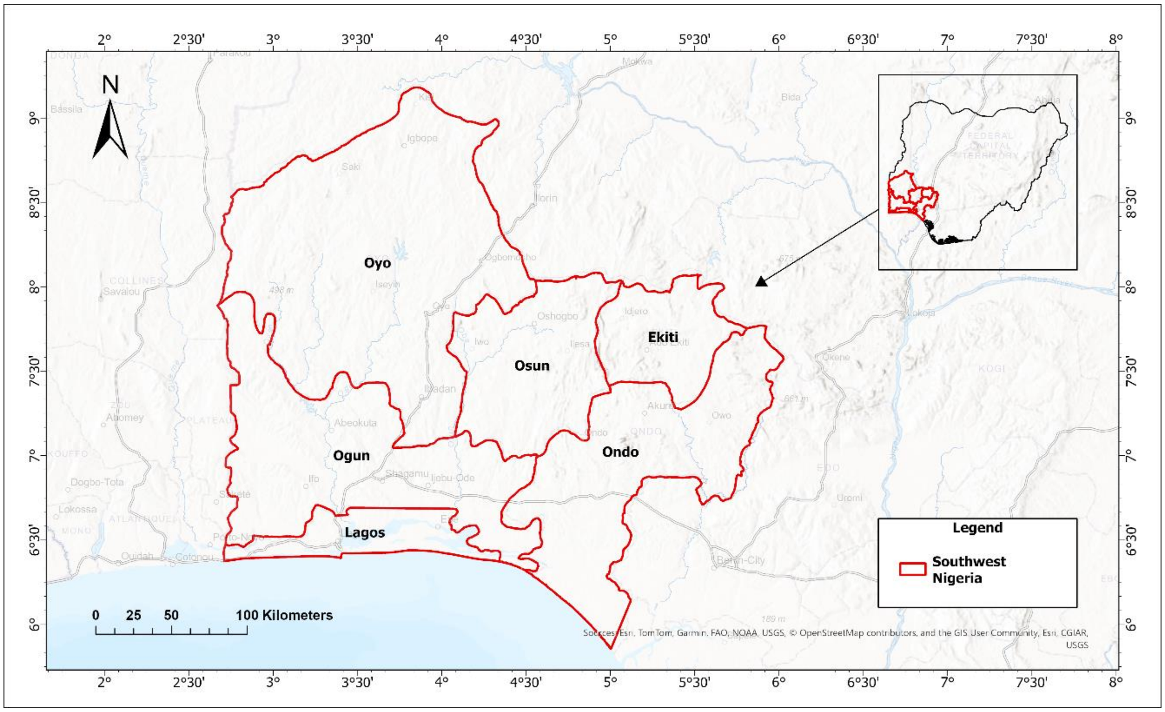

Figure 1: Map of Southwest Nigeria.

2.2 Data Sources

This study utilizes secondary data derived from multiple satellite-based remote sensing platforms, including GEDI LiDAR (25m), Sentinel-1 and Sentinel-2 imagery (10m resolution), ALOS PALSAR (25m), and ancillary datasets such as SRTM (30m), TerraClimate (4km), and OpenLandMap soil (250m). The Coarse-resolution predictors (e.g., TerraClimate ~4 km) were resampled to match higher-resolution datasets, which may introduce smoothing effects. These datasets represent primary observations acquired through spaceborne sensors and provide consistent, large-scale environmental measurements.

This study utilizes independently derived GEDI LiDAR products for both canopy height (RH98) and aboveground biomass density (AGBD), rather than estimating biomass directly from canopy height metrics. This distinction is critical, as it prevents circular relationships between predictor and target variables, ensuring that the observed relationship between canopy structure and biomass reflects actual ecological processes rather than model assumptions. By maintaining this independence, the modelling framework allows for a more reliable assessment of forest structural dynamics and carbon stock changes.

2.3 Data Processing and Extraction

The GEDI LiDAR point cloud canopy relative height (RH98) and Above-Ground Biomass (AGB) metrics were extracted via Google Colab. Precise extraction was achieved using spatial bounding boxes (latitude and longitude), specific granule counts, and annual temporal filters to ensure seasonal consistency. The raw high-density data were subsequently converted from HDF5 (HE.5) format to Comma Separated Values (CSV) to facilitate machine learning integration.

The 38 predictor variables shown in Table 1 were processed at their native resolutions 10m for Sentinel-1/2, 25m for ALOS PALSAR, 30m for SRTM, 250m for OpenLandMap, and ~4km for TerraClimate, using the GEE cloud computing infrastructure. The exported GEDI LiDAR CSV files were imported into the GEE environment, where a sampleRegions function was applied to the RH98 and AGB coordinates. This procedure extracted the exact spectral, radar, topographic, and biophysical values of the predictors at each LiDAR footprint location.

The resulting multi-modal dataset, containing fused structural and environmental features, was exported back to Google Colab for supervised machine learning training, validation, and regional prediction

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	Copernicus S2	Spectral reflectance; vegetation and moisture sensitivity
Vegetation Indices	NDVI, NDMI, NBR	Derived from S2	Canopy greenness, moisture, disturbance detection
SAR (Sentinel-1)	VV, HV, VV/HV	Copernicus S1	Structural information, canopy penetration
SAR (PALSAR)	HH, HV, HH/HV	JAXA PALSAR	Biomass sensitivity, woody structure
SAR Derived Metrics	VV_dB, VH_dB, VV-VH, VH/VV	Sentinel-1	Backscatter intensity, and structural interaction
SAR indices	RVI	Sentinel-1	Canopy density, and structural complexity
SAR Texture GLCM	GLCM contrast, Entropy, Variance	Copernicus Sentinel-1	Captures canopy structure and spatial variability

Terrain	Elevation, Slope, TWI	SRTM DEM	Controls moisture, vegetation distribution
Interaction Features	NDMI_elevation, Elev_slope, Elev_aspect	Derived (S2 & SRTM)	Anchors structural moisture architecture to specific geomorphological positions
Climate	Precipitation, VPD, AET, PET	Terraclimate	Environmental constraints on growth
Soil	Soil Clay, Sand, PH, Bulk density, SOC	SoilGrids	Nutrient and carbon control

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

The modelling framework was implemented in a Python environment using Google Colab and Google Earth Engine (GEE). Canopy height (CHM) and aboveground biomass (AGB) were modelled using machine learning algorithms, specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost) via the Scikit-learn and XGBoost libraries. These algorithms were selected for their robustness in handling the non-linear relationships and high-dimensional datasets characteristic of tropical forest remote sensing. Data manipulation, missing value imputation, and feature engineering (including the derivation of SWIR ratios and SAR composite indices) were performed using Pandas and NumPy. Model diagnostics and feature importance visualizations were generated using the Matplotlib and Seaborn modules. A multi-source predictor dataset was constructed by integrating optical (Sentinel-2), synthetic aperture radar (Sentinel-1 and ALOS PALSAR), topographic (SRTM), and environmental variables (soil and climate). Spectral indices, including NDVI, NDMI, and NBR, were derived to capture vegetation condition, moisture status, and disturbance effects, while SAR-based variables represented canopy structural properties. To improve model generalization and mitigate overfitting, categorical predictors such as land use/land cover (LULC) and spatial coordinates were excluded, ensuring predictions were driven by biophysical relationships. The dataset was randomly split into training (80%) and testing (20%) subsets. Hyperparameters for both algorithms were optimized through iterative tuning to achieve maximum predictive accuracy. The Random Forest model, utilized for canopy height (CHM) estimation, was configured with 500 estimators, a maximum depth of 10, and square-root max features. For aboveground biomass (AGB), the XGBoost regressor was optimized with 1,200 estimators, a learning rate of 0.03, a maximum tree depth of 6, and additional regularization provided by a gamma of 0.2, a minimum child weight of 2, and L2 regularization (lambda = 2).

3.0: Results

3.1 Model Performance

The performance of the canopy height model (CHM) demonstrated moderate accuracy across both study years (Table 2). Both XGBoost and Random Forest models were tested, between the tested algorithms, the Random Forest model achieved the highest performance in 2020, with a coefficient of determination (R^2) of 0.486, accompanied by an RMSE of 3.39 m and MAE of 2.32 m. In 2025, the 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. The inclusion of soil and climate variables for 2025 resulted in a moderate improvement in model performance, increasing R^2 to 0.467, although with a slight increase in RMSE.

In contrast, aboveground biomass (AGB) models exhibited comparatively lower predictive performance (Table 3). Models based solely on structural and spectral predictors showed limited explanatory power, with R^2 values ranging from 0.395 to 0.454. However, the integration of soil and climate variables led to a noticeable improvement in model performance. The highest accuracy was achieved using the XGBoost model for 2025 with environmental predictors, yielding an R^2 of 0.475, RMSE of 25.27 t/ha, and MAE of 18.25 t/ha. While including spatial coordinates (Lat/Lon) as predictors improved model statistics, this study intentionally excluded them to ensure the model captures the biophysical relationships between canopy structure and environmental drivers. This approach enhances the model's transferability and ensures that the detected biomass dynamics are driven by ecological change rather than spatial autocorrelation

Table 2: Canopy Height Model (CHM) Performance

Canopy Height Model	Model	R^2	RMSE (m)	MAE (m)
2020	Random Forest	0.486	3.39	2.32
2025	Random Forest	0.419	2.95	2.23
2025	XGBoost	0.416	2.96	2.24
With Soil and Climate (2025)	XGBoost	0.467	3.49	2.26

Table 3: Aboveground Biomass (AGB) Model Performance

Model Configuration	Model	R^2	RMSE (t/ha)	MAE (t/ha)
Without Soil and Climate (2025)	Random Forest	0.454	25.78	18.73
With Soil and Climate (2020)	XGBoost	0.435	25.01	15.39
With Soil and Climate (2025)	XGBoost	0.475	25.27	18.25

3.1.1 Model Diagnostics and Residual Analysis

The diagnostic plots in Figure 2 show a strong positive relationship between observed and predicted values for both canopy height (CHM) and aboveground biomass (AGB), indicating good model performance across the dataset. For canopy height, predictions closely follow the 1:1 line, although deviations increase at higher values. Similarly, AGB predictions align well with observed values in the low to moderate range, with greater dispersion at higher biomass levels.

Residual plots for both models are generally centered around zero, indicating no substantial systematic bias. However, the spread of residuals increases with predicted values, forming a funnel-shaped pattern. This indicates higher variability in model predictions at greater canopy heights and biomass levels. In addition, a slight underestimation of extreme values is observed, particularly in the upper range of AGB. Overall, the diagnostic results confirm that model accuracy is higher for low to moderate values, with reduced precision at higher structural and biomass ranges.

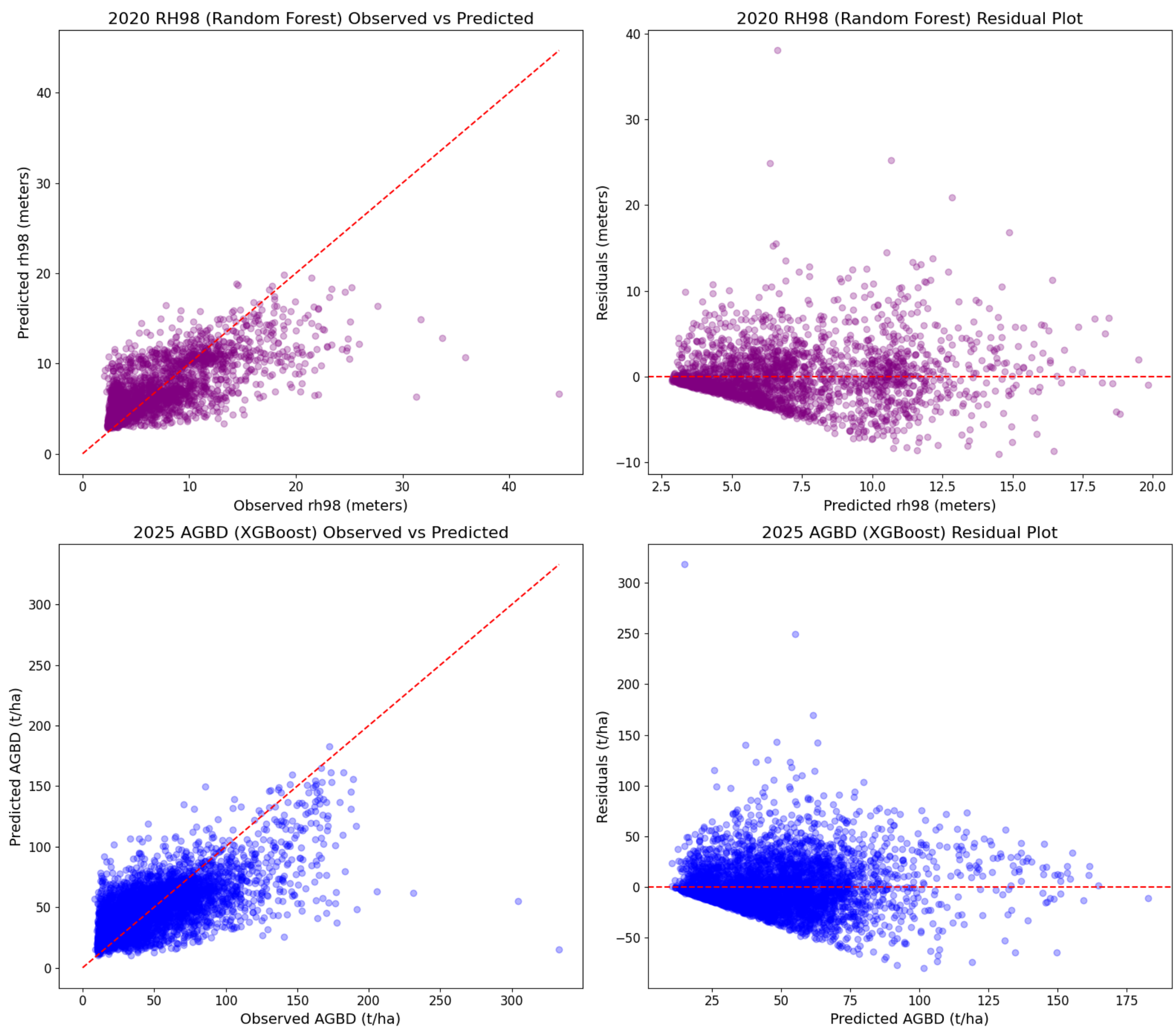

Figure 2 : Model Diagnostics and Residual Analysis Plot of AGBD and CHM

3.2 Drivers of Forest Structure and Biomass

3.2.1 Feature Importance (ML)

Feature importance analysis identified the dominant predictors influencing canopy height and aboveground biomass across the study area. Results presented in Figure 3 indicate that canopy height is primarily controlled by spectral moisture and disturbance-related variables. Specifically, Short-Wave Infrared (SWIR)-based indices—NDMI, B11, and B12—together with the disturbance-sensitive Normalized Burn Ratio (NBR), consistently emerged as the most influential predictors across both 2020 and 2025.

In 2020, NDMI (13.26%), NBR (10.51%), B11 (10.10%), and B12 (8.70%) were the leading predictors, followed by Sentinel-1 VV backscatter (8.63%) and elevation (7.08%). Secondary contributions were observed from B3 (4.91%), NDVI (4.40%), and SAR-based variables such as VH backscatter (3.75%) and PALSAR HV (3.63%).

In 2025, predictor importance became more concentrated, with B12 (29.3%) and B11 (21.3%) dominating the model. Other variables, including elevation (3.58%), PALSAR HV (3.03%), B2 (3.02%), slope (2.94%), NDMI (2.74%), and Sentinel-1 VV (2.70%), played smaller complementary roles. Climate and soil variables had minimal influence on canopy height performance.

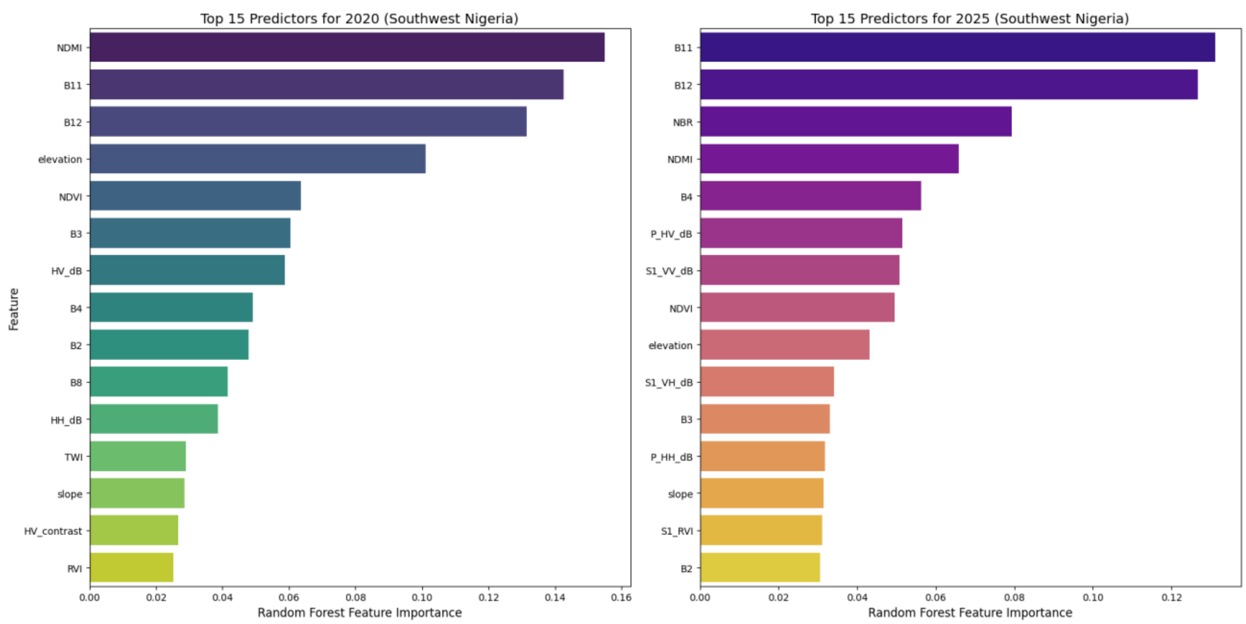

Figure 3: Predictors of canopy height in Southwest Nigeria.

The predictors of aboveground biomass are presented in Figure 4. Unlike the canopy height, aboveground biomass (AGB) exhibited a more complex pattern of predictor influence, reflecting the combined effects of structural and environmental controls. Feature importance analysis revealed that environmental variables, particularly climate and soil predictors, played a significant role in AGB estimation. This is consistent with the observed improvement in model performance, where the inclusion of soil and climate variables increased R^2 from 0.39 to 0.47.

While canopy height was primarily modelled with structural and spectral predictors, the aboveground biomass (AGB) exhibited a more complex pattern of predictor influence, reflecting the combined effects of structural and environmental controls. Similar to canopy height, primary structural proxies derived from Short-Wave Infrared (SWIR) bands, particularly Band 11 (B11) and Band 12 (B12) emerged as the most influential predictors of biomass across both 2020 and 2025

In 2020, biomass prediction was strongly dominated by SWIR-based variables, with B11 (22.50%) and B12 (8.75%) contributing the highest importance. Beyond these structural proxies, environmental variables played a significant role. Climate-related predictors, including vapour pressure deficit (3.56%) and precipitation (3.44%), alongside soil properties such as clay content (2.93%), were among the key contributors. Topographic variables, including slope (3.38%), elevation (2.41%), and terrain-derived interactions (e.g., NDMI–elevation and elevation–slope), also contributed to model performance. In addition, SAR-derived structural variables such as PALSAR HV backscatter (2.21%) provided complementary information on vegetation structure.

In 2025, SWIR variables remained dominant, with B11 (13.17%) and B12 (10.71%) continuing to contribute the largest share of predictive power. However, the model exhibited a broader integration of structural and disturbance-related variables. L-band SAR backscatter (P_HH_dB; 5.73%) and composite SAR metrics (SAR_sum; 5.69%) ranked among the top predictors, indicating increased sensitivity to vegetation structure. Disturbance-related indices such as the Normalized Burn Ratio (NBR; 5.66%) also became more prominent, alongside multi-polarization SAR interactions (S1_VH_VV_ratio; 4.30%). Additional contributions were observed from spectral and environmental variables, including SWIR ratio (3.81%), S1_diff (3.67%), near-infrared band (B8; 3.50%), and precipitation (3.50%).

These results indicate that while biomass estimation is anchored in structural proxies, it is significantly modulated by environmental conditions and disturbance dynamics, highlighting the multi-dimensional controls on biomass distribution.

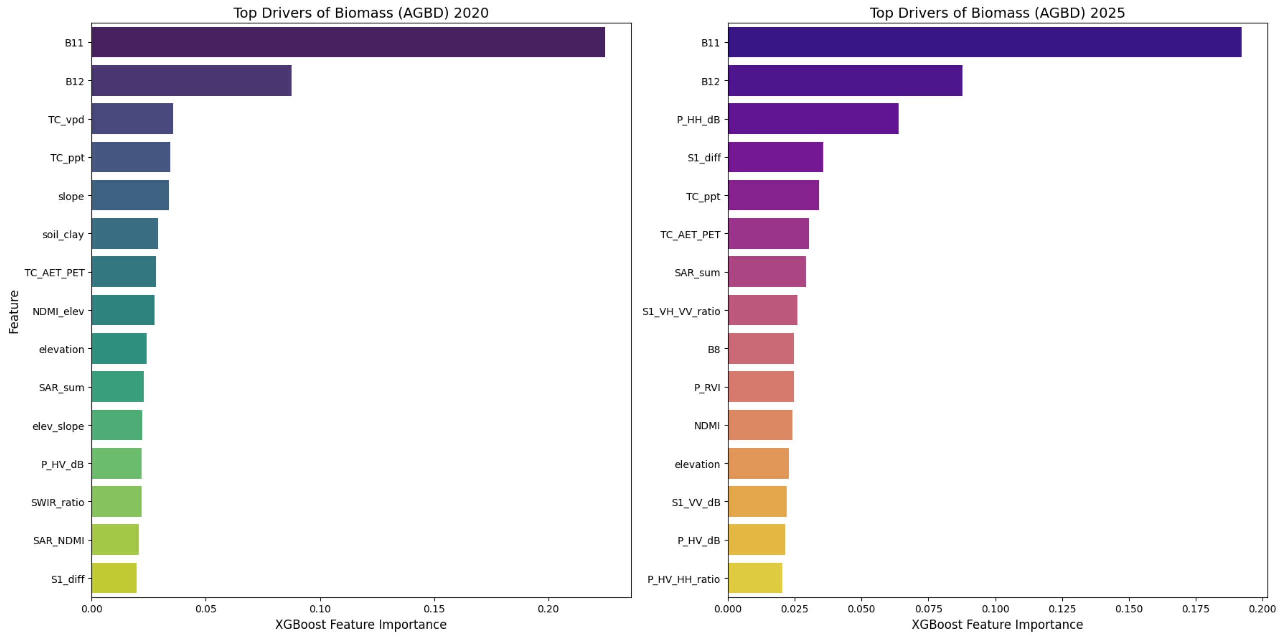

Figure 4: Predictors of aboveground biomass in Southwest Nigeria.

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 Ordinary Least Squares (OLS) regression analysis was conducted to examine the statistical relationships between predictors and canopy height (rh98) for 2025. The model demonstrated moderate explanatory power ($R^2 = 0.343$, $p < 0.001$), indicating that a substantial proportion of canopy height variability is captured by the selected predictors.

The results highlight the dominant influence of SWIR-based variables, with Band 12 ($\beta = 119.91$, $p < 0.001$) and Band 11 ($\beta = -95.92$, $p < 0.001$) emerging as the strongest predictors. Disturbance-related dynamics were also significant, as indicated by the positive effect of the Normalized Burn Ratio (NBR; $\beta = 46.70$, $p < 0.001$). Moisture-related variability, captured by NDMI ($\beta = -39.05$, $p < 0.001$), further influenced canopy structure.

In addition, topographic factors such as slope and elevation exhibited significant positive relationships with canopy height, while SAR-derived volume scattering (P_HV_dB) contributed modestly to the model. These findings reinforce the importance of spectral moisture indicators, disturbance signals, and terrain characteristics in explaining canopy height variability.

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

Variable	Coefficient (β)	Significance	Interpretation
B12	119.91	$p < 0.001$	Strong structural/moisture proxy
B11	−95.92	$p < 0.001$	Moisture gradient effect
NBR	46.7	$p < 0.001$	Disturbance recovery signal
NDMI	−39.05	$p < 0.001$	Moisture–structure interaction
B2	66.65	$p < 0.001$	Reflectance contribution
B3	−73.84	$p < 0.001$	Vegetation reflectance contrast
B4	23.08	$p < 0.001$	Red band contribution
Slope	0.102	$p < 0.001$	Terrain influence
Elevation	0.0017	$p < 0.001$	Topographic control
P_HV_dB	0.18	$p < 0.001$	Volume scattering (structure)

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 (AGB) for 2025. The model demonstrated moderate explanatory power ($R^2 = 0.388$, $p < 0.001$), indicating that a substantial proportion of biomass variability is captured by the selected predictors.

The results reveal a strong dominance of SWIR-based structural variables, with Band 12 ($\beta = 2645.34$, $p < 0.001$) and Band 11 ($\beta = -1733.75$, $p < 0.001$) emerging as the most influential predictors. Disturbance-related dynamics were also highly significant, as indicated by the positive effect of the Normalized Burn Ratio (NBR; $\beta = 1245.80$, $p < 0.001$), while moisture-related variability captured by NDMI ($\beta = -965.25$, $p < 0.001$) further influenced biomass distribution.

Structural contributions from SAR data were also evident, with L-band backscatter (P_HH_dB) and multi-polarization interactions (S1_VH_VV_ratio) playing significant roles. In addition, environmental controls were strongly represented, with precipitation (TC_ppt), water balance

(TC_AET_PET), and soil clay content significantly influencing biomass variability. Topographic variables, including elevation and slope, also contributed to the spatial distribution of biomass.

Table 5: Significant OLS Aboveground biomass (2025)

Variable	Coefficient (β)	Significance	Interpretation
B12	2645.34	$p < 0.001$	Strong structural/moisture proxy
B11	−1733.75	$p < 0.001$	Moisture gradient effect
NBR	1245.8	$p < 0.001$	Disturbance recovery
NDMI	−965.25	$p < 0.001$	Moisture–structure interaction
P_HH_dB	2.56	$p < 0.001$	L-band structural signal
P_HV_dB	−1.92	$p < 0.001$	Structural contrast
SAR_sum	0.65	$p < 0.001$	Composite SAR structure
SAR_diff	−4.48	$p < 0.001$	Structural variability
S1_VH_VV_ratio	−151.65	$p < 0.001$	Multi-polarization structure
TC_AET_PET	−199.98	$p < 0.001$	Water balance constraint
TC_ppt	0.029	$p < 0.001$	Precipitation effect
Soil_clay	−0.50	$p < 0.001$	Soil limitation
Elevation	−0.106	$p < 0.001$	Terrain constraint
Slope	0.662	$p < 0.001$	Terrain influence
NDMI_elev	0.258	$p < 0.001$	Interaction effect
SAR_NDMI	6.7	$p < 0.001$	Structure–moisture interaction

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.

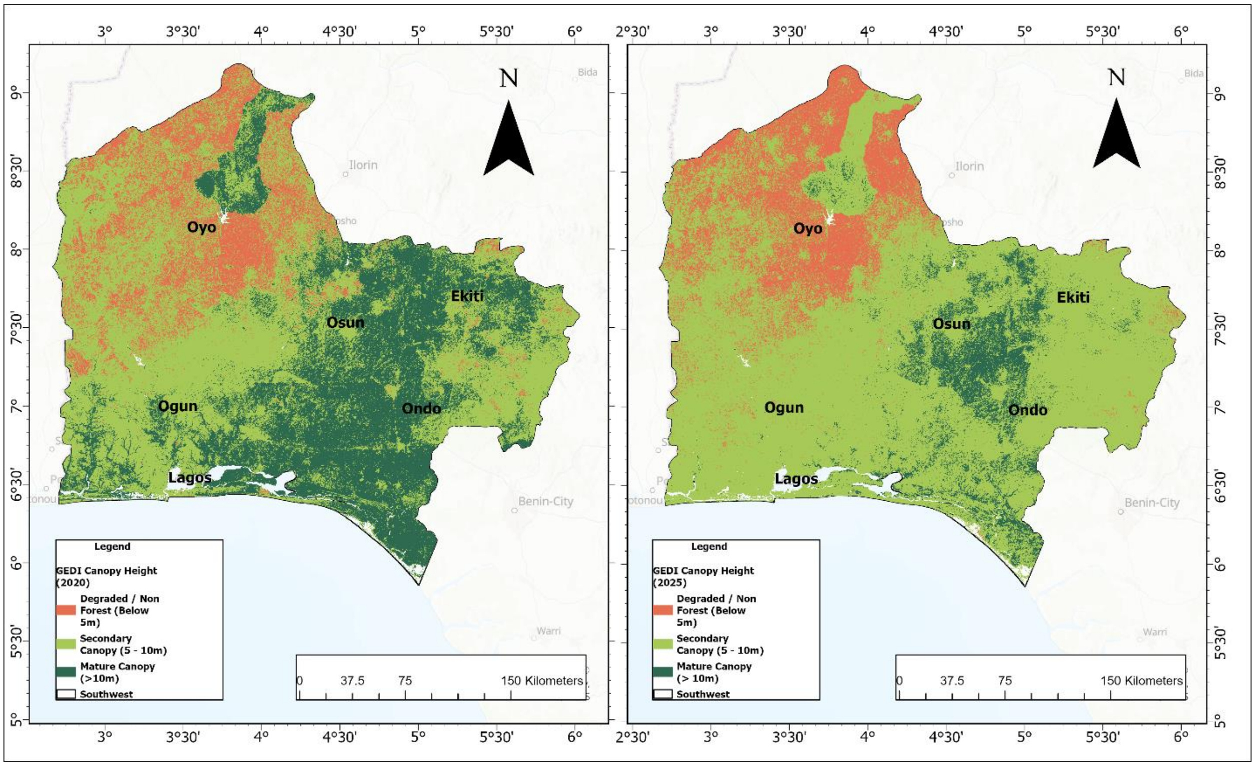

Figure 5: Change in Canopy Height from 2020 to 2025.

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.

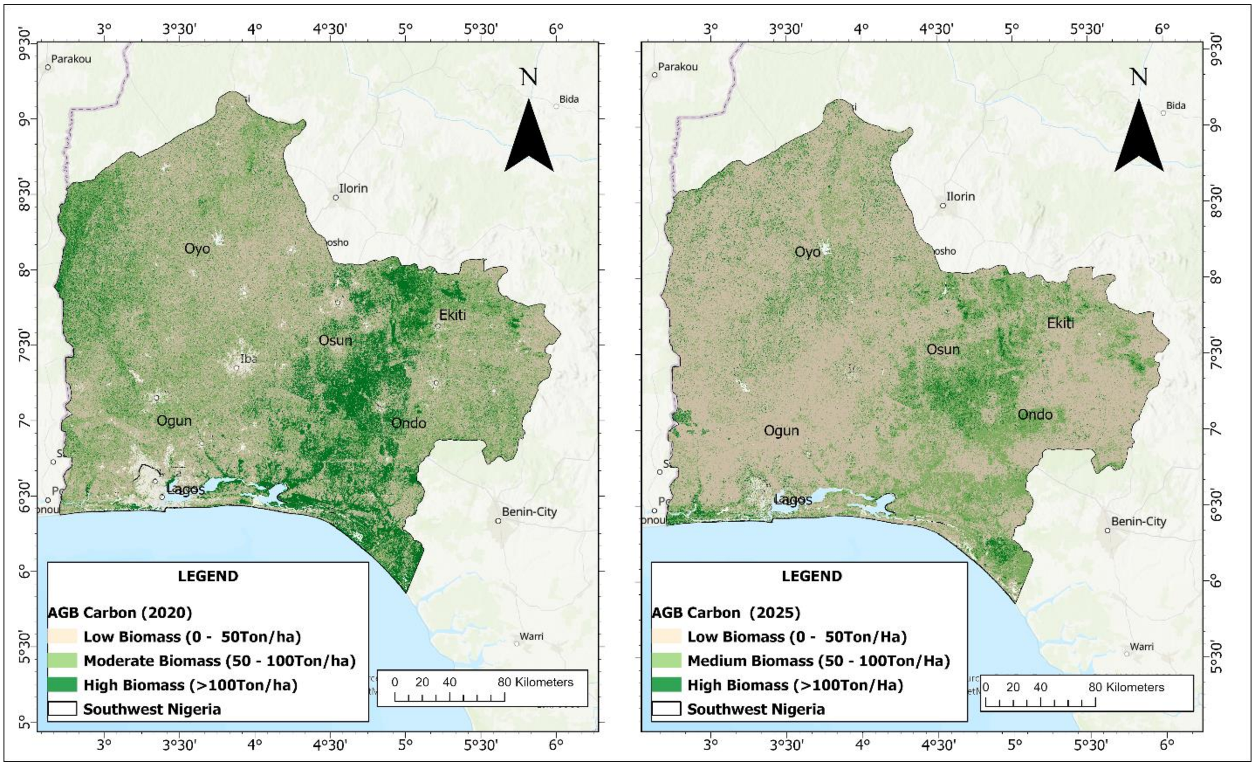

Figure 6: Change in Aboveground biomass from 2020 to 2025.

The aboveground biomass in South West Nigeria declined from 64.89 ± 44.50 ton/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 high canopy height generally coincide with areas of high biomass, particularly in the southern forest belt, whereas areas with low canopy height are largely associated with low biomass, especially in the northern part of the region. Intermediate canopy height classes in the central zone similarly 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, canopy height declined across all states by about 10–23%, whereas aboveground biomass decreased more strongly, by about 20–39%. This shows that biomass loss exceeded canopy height reduction throughout the region. Thus, while the two independently modelled surfaces remain spatially related, their temporal responses were not proportional, with AGB showing greater sensitivity to forest change than CHM

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 landscape.

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 Decoupling Canopy Height Model and Above-Ground Biomass

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. In many areas, forests retain moderate canopy height while experiencing substantial reductions in biomass, suggesting the loss of tree density, reduced stem volume, and simplified canopy architecture. This pattern reflects degradation processes such as selective logging, fragmentation, and sub-canopy disturbance, which reduce biomass without necessarily causing immediate reductions in canopy height.

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.

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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