Assessing canopy height and aboveground biomass dynamics in Southwestern Nigeria using GEDI LiDAR and multi-sensor Earth observation

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This paper has been submitted to Environmental Monitoring and Assessment

Abstract:

Accurate monitoring of forest degradation is important for understanding changes in forest carbon storage and associated carbon losses. Although canopy height derived from spaceborne LiDAR provides an important indicator of forest structural condition, estimating canopy height, biomass and detecting their changes in structurally complex tropical forests remain challenging. This study developed a multisensor satellite-fusion approach to predict canopy height and AGB in the tropical forests of Southwestern Nigeria between 2020 and 2025 using GEDI LiDAR and multi-sensor Earth observation 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 = 0.44–0.48 for AGB). Independent comparison with the GLULC canopy-height product (Potapov, 2021) and the ESA CCI biomass product (Santoro and Cartus, 2023) showed moderate and strong positive agreement, with correlation coefficients of R = 0.56 and R = 0.79, respectively.

Both canopy height and AGB declined between 2020 and 2025, with all six states in Nigeria's Southwestern rainforest recording reductions in forest canopy height and aboveground biomass. Biomass-derived CO_2-equivalent stock density decreased from 384.68 $MgCo_2e$/ha in 2020 to 336.87 $MgCo_2e$/ha in 2025, which represents a reduction of 47.81 $MgCo_2e$/ha (12.43%).

These findings demonstrate the value of integrating biomass indicators for characterising forest degradation and carbon dynamics. The decline in biomass and associated CO_2-equivalent stocks highlights implications for Nigeria's REDD+ efforts. GEDI LiDAR and multi-sensor Earth observation data provide a scalable approach for monitoring forest structure, biomass, and carbon dynamics.

Keywords: Forest degradation, Canopy Height Model (CHM), Multi-sensor data fusion, Carbon storage, Aboveground biomass

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 reduce forest structural integrity and weaken 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 changes between 2020 and 2025, and (iii) assess the implications of observed changes in canopy structure and aboveground biomass for forest condition and associated carbon stocks.

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 as shown in Fig 1. It is 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.

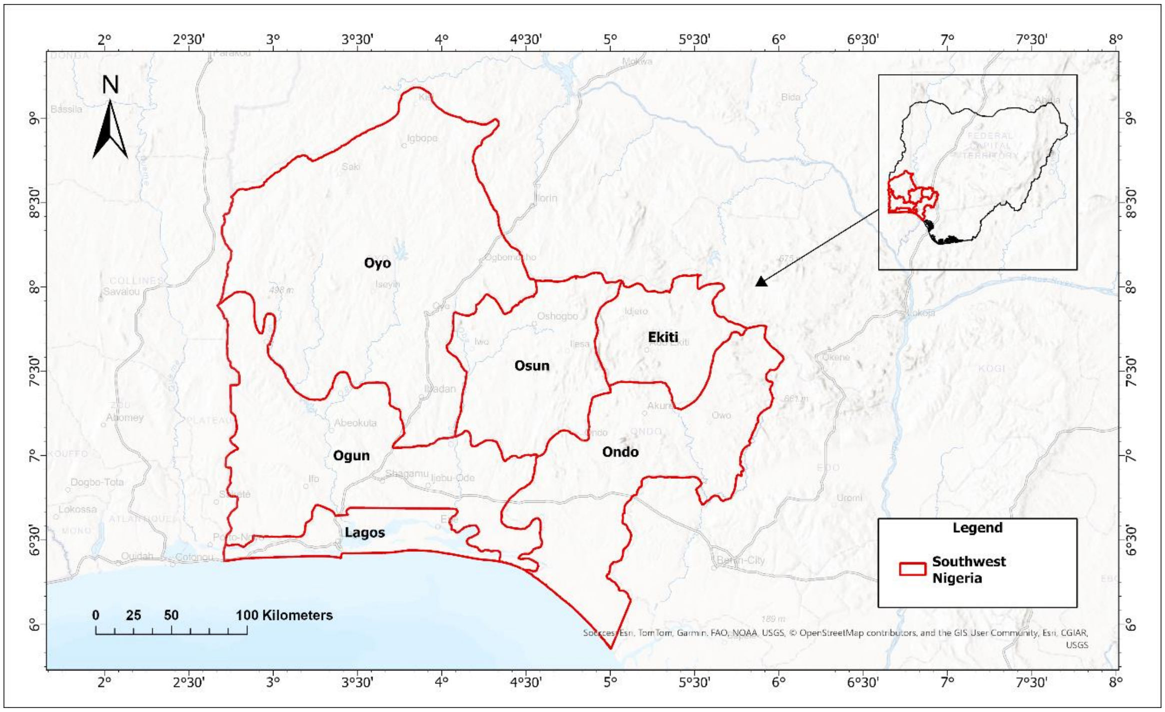

Fig 1: Map of Southwest Nigeria.

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. Data Extraction

The study extracted the GEDI L2A and L4A using the Application Programming Interface (API), executed using the Python programming language in Google Colab. The GEDI observations were filtered using quality_flag = 1 and sensitivity (0.90). GEDI observations intersecting the Southwest Nigeria Shapefile. The GEDI footprints of GEDI L2A and GEDI L4A for 2020 and 2025 were extracted from HDF5 files, converted and saved as comma-separated values (CSV) file.

A total of 370,316 and 123165 GEDI L2A (RH98) were extracted for 2020 and 2025, respectively. Similarly, a total of 89, 899 and 87400 GEDI L4A observations were extracted for 2020 and 2025, respectively.

The geographic coordinates of the extracted GEDI observations were subsequently used as sampling locations for extracting multisensor predictor variables, including optical spectral, radar, elevation, and climate, using the sample region function in Google Earth Engine. The resulting predictor datasets were used for machine-learning modelling and subsequent production of final Aboveground biomass and canopy height maps for the study area.

2.6. 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 (70%) and testing (30%) subsets, and model performance was evaluated using R^2, RMSE, and MAE. Moreover, the modelled aboveground biomass (AGB) and Canopy Height Model (CHM) were compared with the European Space Agency's Climate Change Initiative Biomass (ESA CCI) (Santoro and Cartus, 2023) and Global land cover and land use change (Potapov et al., 2021) as an external benchmark.

2.7. Conversion of Aboveground Biomass to CO_2 Equivalent

To quantify the carbon dioxide equivalent associated with the estimated aboveground biomass (AGB), this study adopted the Intergovernmental Panel on Climate Change (IPCC, 2006) guideline for converting biomass carbon stocks to equivalent carbon dioxide. The carbon fraction of 0.47 Mg C per Mg dry biomass for tropical and subtropical forest biomass was adopted. The biomass carbon stock was then converted to CO2 equivalent using the molecular mass ratio of 44/12. Equations 1- 3 show the sequential equations used to convert aboveground biomass to CO_2 equivalent

$$C = AGB \times 0.47 \quad (1)$$

$$CO_2 = \frac{44}{12} \quad (2)$$

$$CO_2e = AGB \times 0.47 \times \frac{44}{12} \quad (3)$$

Where AGB is aboveground biomass (Mg/ha), C is biomass carbon stock (Mg C/ha), 0.47 is the adopted carbon fraction of dry mass, 44/12 is the molecular mass ratio of CO2 to C, and CO_2e represents the CO_2e equivalent associated with the estimated biomass carbon stock (Mg CO_2e/ha).

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, including environmental predictors improved model performance, while excluding spatial coordinates ensured 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 Fig. 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 centred 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.

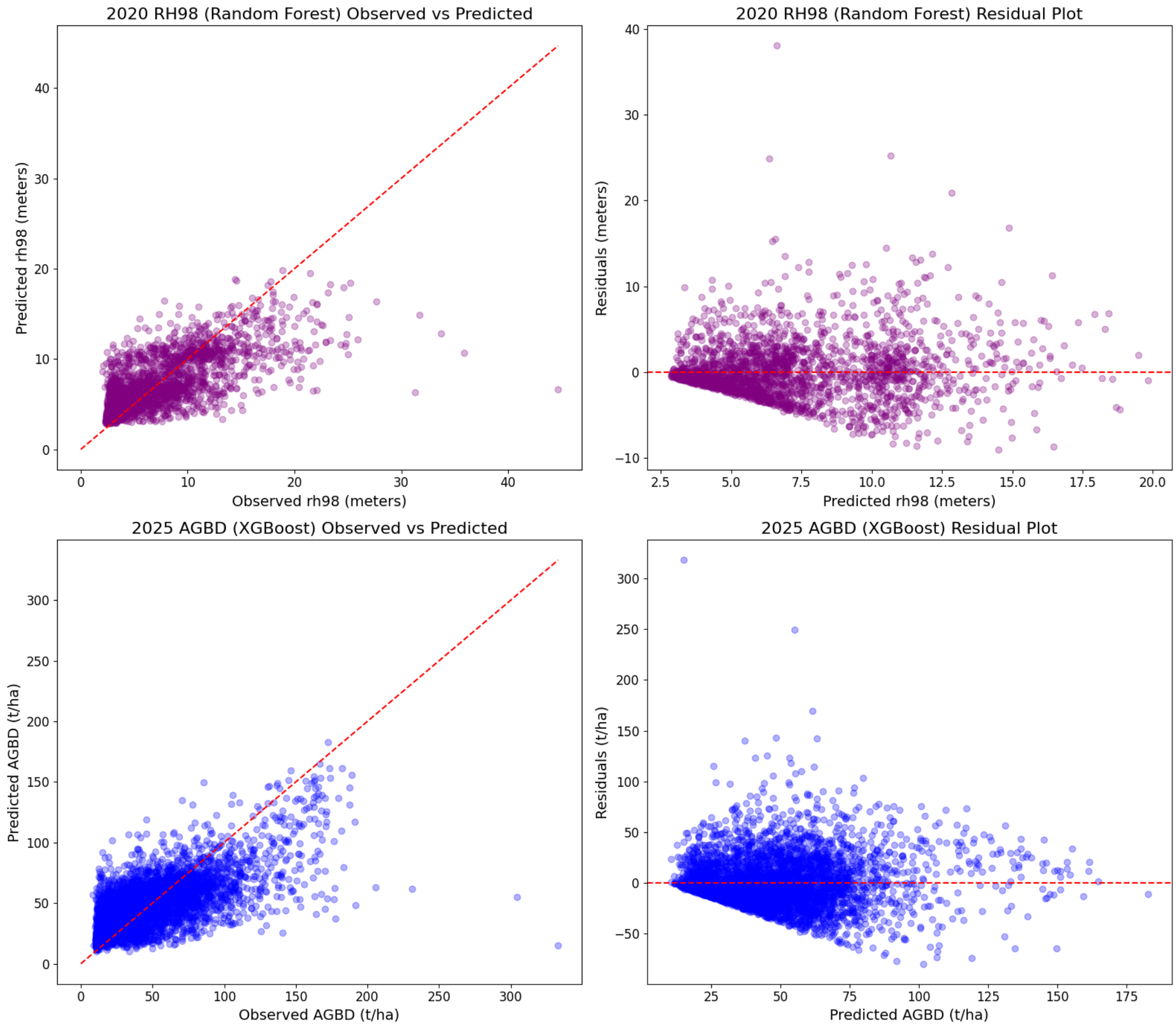

Fig 2: Model Diagnostics and Residual Analysis Plot of AGBD and CHM

External Benchmark Assessment of Modelled CHM and AGB

The Predicted Canopy Height Model recorded a mean value of 8.36m, while the GLCLU recorded a lower mean of 8.32m. A moderate relationship is found between the two datasets (Pearson R = 0.56, R^2 = 0.31, MAD = 3.91m, and RMSE = 4.83 m). The predicted CHM showed a positive mean bias of 2.93m, signifying that the locally calibrated CHM recorded higher values than the benchmarked Global Land Use Land Cover (GLULC) model (Peterpov et al, 2021).

The locally modelled aboveground biomass recorded a mean of 33.84 Mg/ha, with a strong positive correlation with the European Space Agency Climate Change Initiative Biomass ESA CCI (Pearson R = 0.79, R^2 = 0.62). The mean absolute difference was 23.83 Mg ha^{-1}, while the RMSE was 33.52 Mg ha^{-1}. The model exhibited a bias of -11.57 Mg/ha, indicating that the locally modelled values are generally lower compared to the ESA CCI.

Table 3: Comparison between locally predicted CHM and AGB, with external benchmark

Metric	CHM: Local model vs GLULC	AGB: Predicted vs ESA CCI
Local/Predicted mean	8.36 m	33.84 Mg/ha
Benchmark mean	8.33 m	35.23 Mg/ha
Pearson r	0.56	0.79
R^2	0.31	0.62
Bias	2.93m	−11.57 Mg/ha
MAD (Mean Absolute Difference)	3.91 m	23.83 Mg/ha
RMSE	4.83 m	33.52 Mg/ha

3.2 Predictors of Forest Structure and Biomass

3.2.1 Feature Importance of Canopy Height Model

Feature importance analysis identified the dominant predictors associated with canopy height across the study area (Fig. 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.

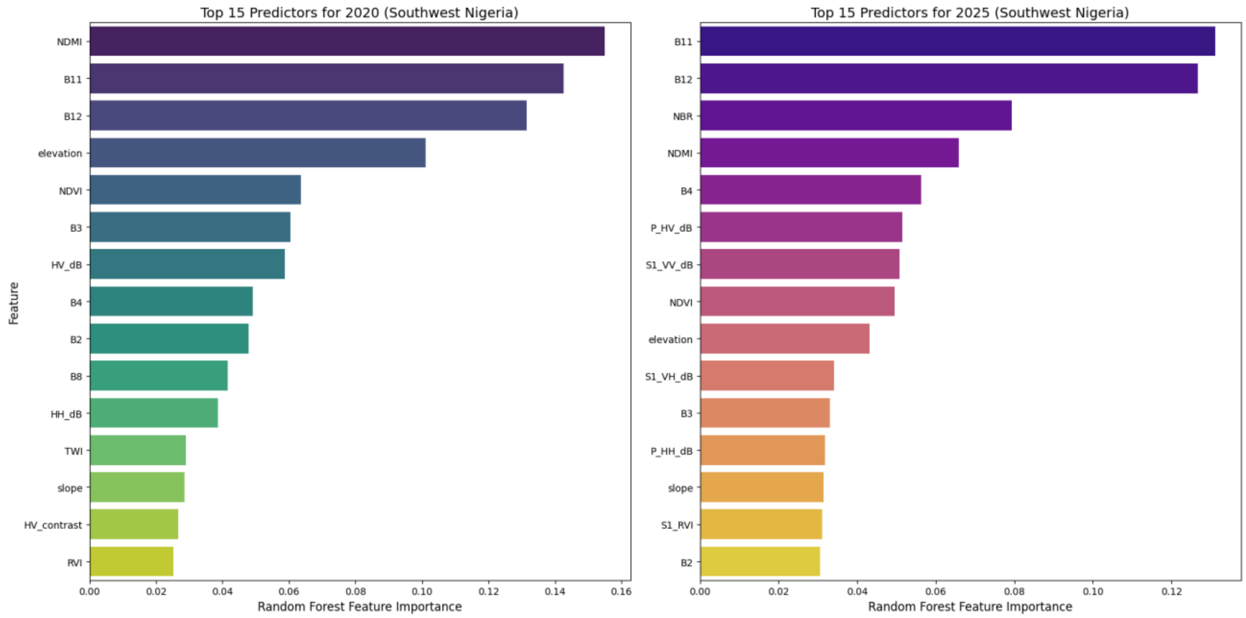

Fig 3: Predictors of canopy height in Southwest Nigeria.

3.2.2. Feature importance of Aboveground biomass

The predictors of aboveground biomass are presented in Fig 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.

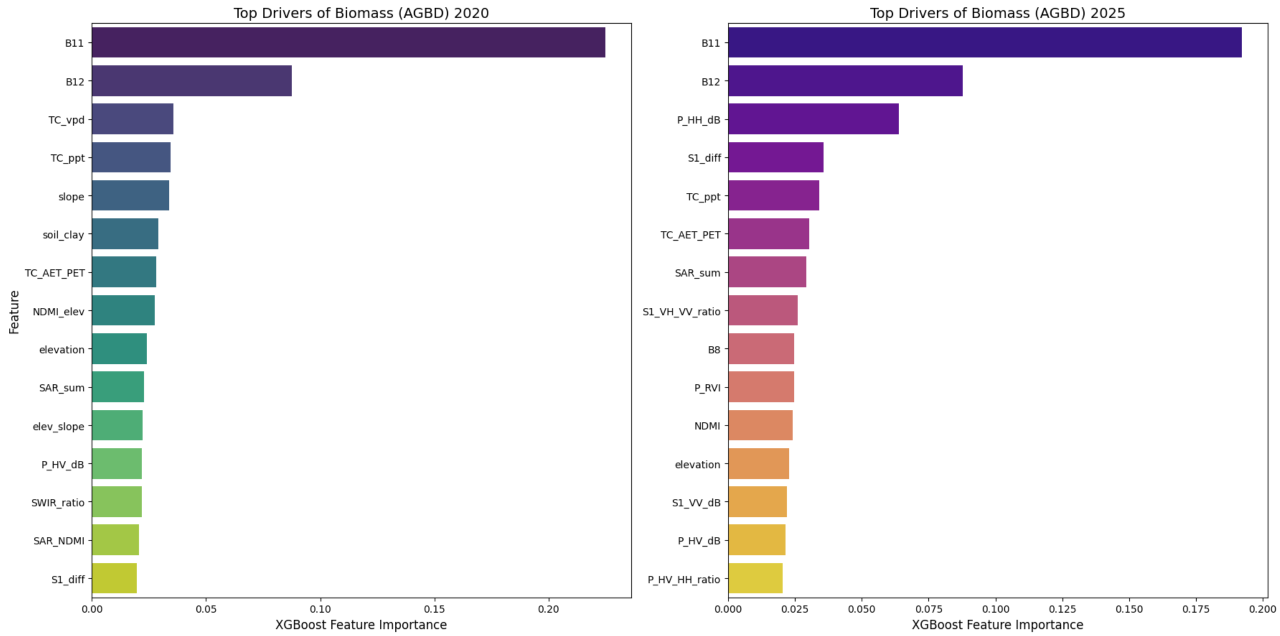

Fig 4: Predictors of aboveground biomass in Southwest Nigeria

3.3. Spatiotemporal Change in canopy height from 2020 to 2025

Figure 5 shows the change in canopy height from 2020 to 2025. In 2020, tall canopy ranges were observed in Ekiti, Osun, and Ondo states, Nigeria, while Oyo, Ogun, and Lagos states exhibited lower canopy height values. By 2025, the spatial extent of these regions, particularly Osun, Ekiti, and Ondo, as well as Oyo State Forest parks, had decreased. The comparison shows spatial-temporal change in forest canopy height across the two study periods.

The average canopy height 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.

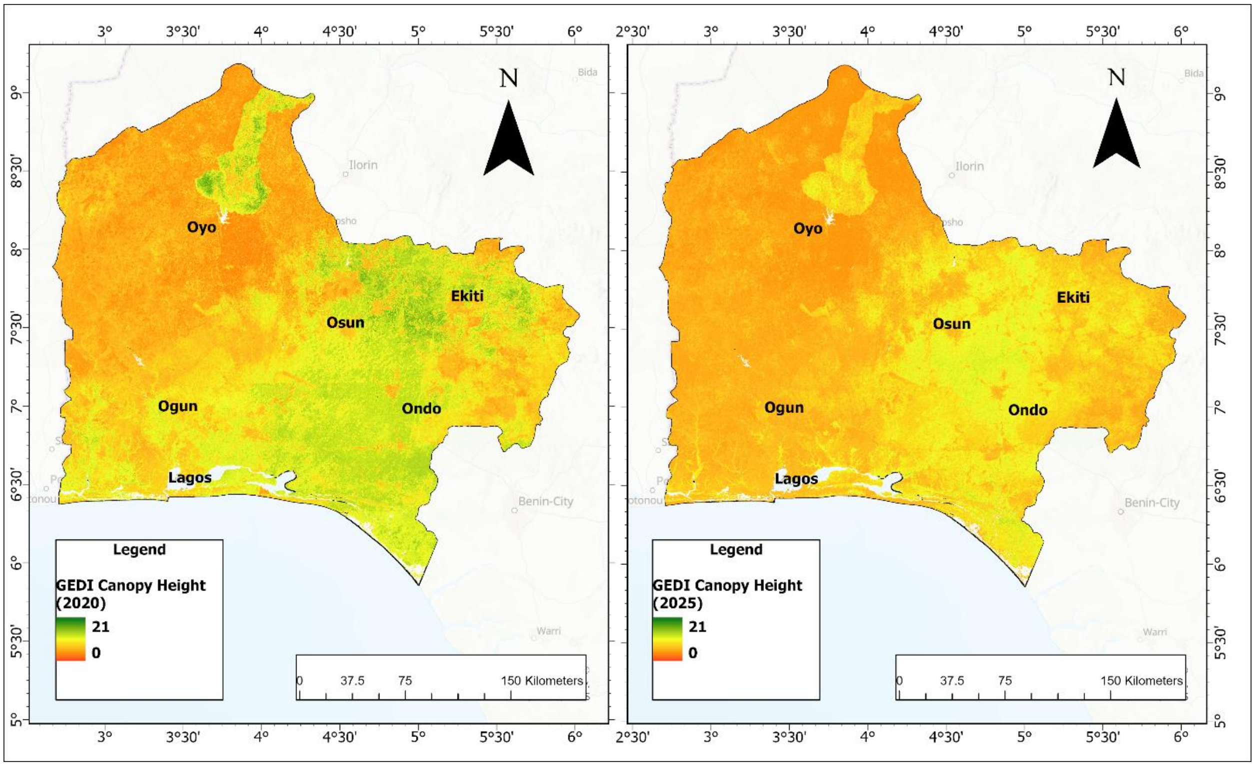

Fig 5: Change in Canopy Height from 2020 to 2025.

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 Fig. 6 revealed substantial declines across Southwest Nigeria between 2020 and 2025. The southwestern rainforest of Nigeria recorded an average aboveground biomass of 35.23±14.33Mg/ha. The aboveground biomass value reduced to 30.32 ± 10.66 Mg/ha by 2025, marking a 13.95% reduction over the 5 years.

In 2020, high biomass was concentrated in the southern region (Ondo, southern Ogun, Lagos, and Northern old Oyo Park). By 2025, high biomass areas became fragmented and reduced, with moderate and low biomass classes expanding across the region. While the Aboveground biomass and the canopy height were modelled independently, the pattern of reduction in the two forest structures exhibited biomass depletion and structural degradation.

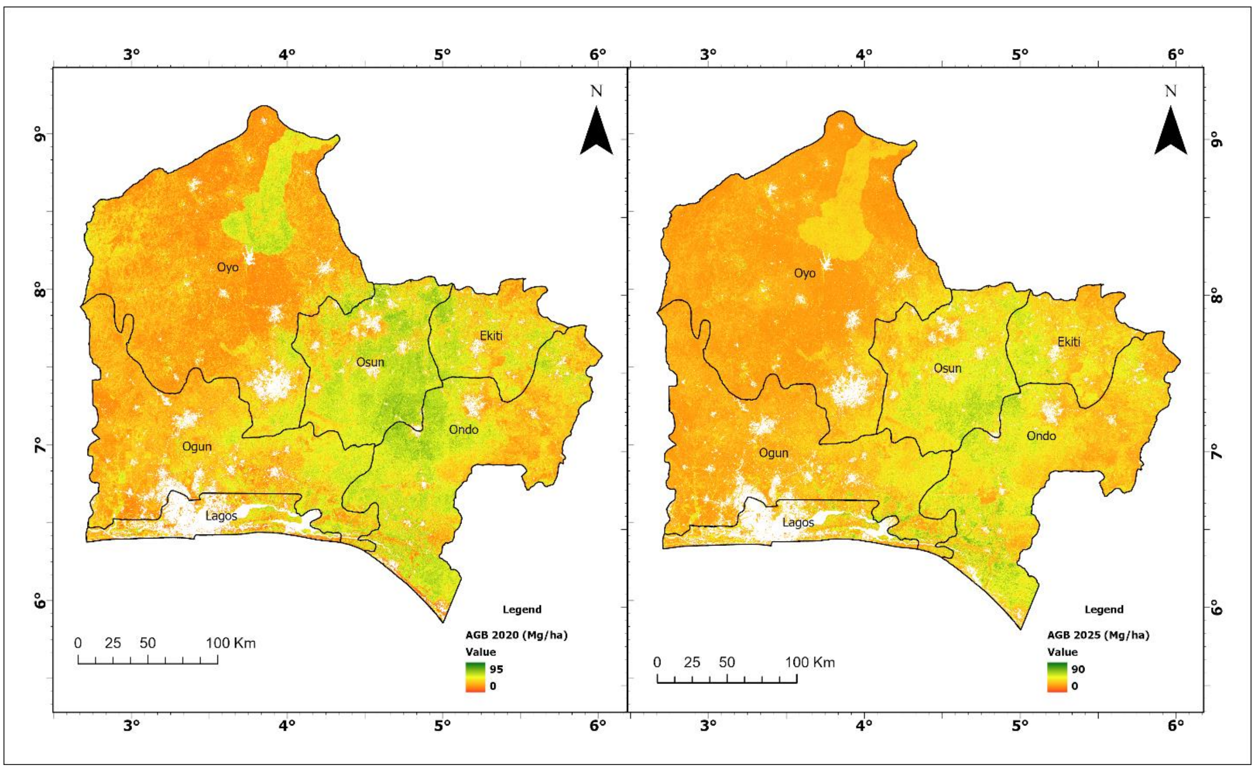

Fig 6: Change in Aboveground biomass from 2020 to 2025.

Table 7 represents the 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 (48.09 Mg/ha), followed by Ondo (41.97 Mg/ha), Ekiti (40.13 Mg/ha), Lagos (32.35 Mg/ha), Ogun (32.21 Mg/ha), and Oyo (28.45 Mg/ha).

By 2025, mean biomass values decreased across all states, with Osun still having the highest value (39.72 Mg/ha), followed by Ondo (36.98 Mg/ha), Ekiti (35.21 Mg/ha), Lagos (31.52 Mg/ha), Ogun (27.99 Mg/ha), and Oyo (24.04 Mg/ha).

At the regional scale, the greatest loss is recorded in Osun, Ondo, Ekiti, Oyo and Ogun, with a negligible loss in Lagos. The mean aboveground biomass declined from 35.23 ± 14.33 Mg /ha in 2020 to 30.32 ± 10.66 Mg /ha in 2025, corresponding to a 13.93% reduction. The decline in regional mean aboveground biomass was accompanied by a reduction in biomass-associated CO_2-equivalent stock density from approximately 60.70 Mg CO_2e/ha in 2020 to 52.24 Mg CO_2e /ha in 2025. Based on the aggregated state-level estimates, the corresponding CO_2-equivalent stock declined from 384.68 Mg CO_2e/ha in 2020 to 336.87 Mg CO_2e/ ha in 2025, representing a reduction of 47.81 Mg CO_2e/ha.

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

State	AGB 2020 (Mg/ha)	AGB 2025 (Mg/ha)	AGB Loss (Mg/ha)	% Change	CO_2e 2020 (Mg/ha)	CO_2e 2025 (Mg/ha)	CO_2e Loss (Mg/ha)
Osun	48.09	39.72	8.37	17.40%	82.88	68.46	14.43
Ondo	41.97	36.98	4.99	11.89%	72.33	63.73	8.60
Ekiti	40.13	35.21	4.92	12.26%	69.16	60.68	8.48
Oyo	28.45	24.04	4.41	15.50%	49.03	41.43	7.60
Ogun	32.21	27.99	4.22	13.10%	55.51	48.24	7.27
Lagos	32.35	31.52	0.83	2.57%	55.75	54.32	1.43
TOTAL	**223.2**	**195.46**	**27.74**	**0.7272**	**384.68**	**336.87**	**47.81**

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.

Comparison with the independent benchmark CHM showed a moderate spatial association ($r = 0.56$; $R^2 = 0.31$). The locally modelled CHM was, on average, 2.93 m higher than the benchmark, with a mean absolute difference of 3.91 m and an RMSE of 4.83 m. These statistics indicate the magnitude and spatial consistency of differences between the two independently derived products rather than model error relative to ground truth, since the benchmark is itself a remotely sensed/model-derived product

Relative to the ESA CCI benchmark, the locally modelled AGB showed a negative mean difference of −11.57 Mg ha^{-1}, indicating that the local estimates were generally lower than the benchmark product. Because ESA CCI is itself a model-derived biomass product rather than ground-truth observations, this difference should be interpreted as an inter-product discrepancy rather than definitive evidence of model underestimation.

The relatively strong spatial association ($r = 0.79$; $R^2 = 0.62$) indicates that the two products captured broadly similar spatial patterns, whereas the differences in absolute magnitude, reflected by the MAD and RMSE, indicate areas of substantial disagreement.

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

4.2 Predictors of forest structure and aboveground biomass

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 aboveground 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. Change in spatio-temporal canopy height, aboveground biomass and carbon implications

The spatio-temporal analysis of canopy height and aboveground biomass across the Southwestern rainforest region of Nigeria indicates a general reduction between 2020 and 2025. The decline in regional mean aboveground biomass was accompanied by a reduction in biomass-associated CO_2-equivalent stock density from approximately 60.70 Mg CO_2e ha^{-1} in 2020 to 52.24 Mg CO_2e ha^{-1} in 2025, highlighting the implications of declining forest biomass for carbon storage.

The concurrent decline in forest height and aboveground biomass is consistent with a reduction in forest structural condition, biomass stock and associated CO2-equivalent during the study period. Although the present analysis does not directly attribute these changes to specific drivers, the observed decline is consistent with documented human and climatic pressures affecting forests in Southwestern Nigeria.

According to federal ministry of Environment, National Forest Emission Level (FREL, 2026), the rainforest-savanna ecological region of Nigeria is the most vulnerable to deforestation and forest degradation. Similarly, Fashona et al. (2020) documented deforestation associated with land use/land cover changes in southwestern Nigeria from 1986 to 2016, with more pronounced forest loss in later years from 2006 to 2016. The depletion of economically important trees like Milicia species, Triplochiton sceroxylon, Khaya species, and Mansonnia species has also been reported in the southwestern rainforest region (Alamu and Agbeja, 2011). Furthermore, Bejide (2026) reported an association between forest disturbance, represented by NBR, moisture stress, and vegetation browning in Ibadan within the forest–savanna transition region of Southwestern Nigeria.

Overall, the results demonstrate that the decline in canopy height and biomass is associated with a reduction in CO2-equivalent in the southwestern rainforest ecological belt of Nigeria. The observed reduction in aboveground biomass and associated CO_2-equivalent stocks highlights the implications of continued forest degradation and deforestation for Nigeria's efforts to reduce emissions from deforestation and forest degradation (REDD+) and achieve forest-based climate-change mitigation goals.

5.0 Conclusion

This study demonstrates a 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 13.95%.

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 state-wide total reduction in CO2-equivalence from 384.68 $MgCo_2e$/ha in 2020 to 336.87 $MgCo_2e$/ha in 2025 underscores a substantial loss in carbon storage capacity.

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

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 generalisation, 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

Funding: This study received no external funding

Research and publication ethics statement: In the study, the authors declare that there is no violation of research and publication ethics and that the study does not require ethics committee approval.

Conflicts of Interest: The authors declare no conflicts of interest.

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.

Declaration of generative AI use.

During the preparation of this work, the author(s) used Google Gemini to correct 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.

A preprint version of this manuscript has been previously published on EarthArXiv (Bejide et al., 2026). The present submission represents a revised and expanded version with additional analyses and methodological improvements

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