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ABOVEGROUND BIOMASS ALLOMETRIC MODELS FOR A PRIVATE SEMI-NATURAL FOREST IN NIGERIA

Alade A.A.[1], Oluwajuwon T.V.[1*], Alo A.A.[1], Ogana F.N.[1], and Aghimien E.V.[2]

[1]Department of Social and Environmental Forestry, University of Ibadan, Ibadan, Nigeria
[2]Forestry Research Institute of Nigeria, Moist Forest Research Station, Benin, Nigeria
[*]**Corresponding Author:** *tomiwaoluwajuwon@gmail.com;* +234 810 020 5306

ABSTRACT

Private forests with conservation priority such as Abayomi Farm Estate (AFE) Emerald forest reserve, Nigeria can significantly contribute to the global carbon cycle while enhancing sustainable livelihoods. However, little consideration is given to accounting for their biomass pools and carbon sequestration. This study, therefore, developed models for estimating aboveground biomass in the private semi-natural forest. Four (4) temporary sample plots (TSPs) of 50 x 50 m were systematically sampled with a complete, non-destructive enumeration of 176 individual tree species with a diameter at breast height (DBH) > 10 cm. Aboveground biomass models were developed using the enumerated parameters covering a wide range of DBH and total height (H), as well as wood density (WD) as predictor variables. The models were developed for the two most-abundant, native tree species and all species combined in the forest. The models were evaluated using different indices such as coefficients of determination (R^2), root mean square error (RMSE). Selected models were cross-validated. The species-specific biomass models with double predictors proved more accurate and reliable for estimating aboveground biomass in the forest than the DBH-only allometry, with their adjusted R^2 as high as 95 % and RMSE < 0.23. Mixed-species allometry fitted by all the three predictors (DBH, H and WD) was the most suitable, depicting the added relevance of wood density and sample size in biomass modelling. It recorded RMSE and adjusted R^2 of 0.22 and 97 %, respectively. Overall, all the models provided good estimates and could be used for assessing the carbon storage in the forest estate.

Keywords: Aboveground biomass, allometric model, non-destructive technique, forest carbon, *Cola gigantea*, *Picralima nitida*

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INTRODUCTION

The significance of tropical forests in the global carbon cycle cannot be overemphasized. These forest ecosystems play important role in climate change mitigation by sequestering carbon from the atmosphere (Mitchard *et al*., 2018; Baccini *et al*., 2017). As such, about 50% of global carbon is stocked in tropical forests while a majority (60%) of the carbon is found in the aboveground biomass of the forests (Pan *et al*., 2011). The carbon sequestered by the trees during the photosynthesis process is stored as part of their structural biomass, constituting approximately 50% of the dry biomass, which makes them a considerable carbon sink (Brown, 1997). However, tropical forests have also been a major net carbon source through the increasing rates of deforestation and degradation, estimated to account for 7-15% of the total anthropogenic CO_2 emissions (Mitchard *et al*., 2018; FAO, 2015). This has greatly posed challenges to its dynamics and productivity, as well as attracted increasing concerns in the global community (Hossain *et al.*, 2023a; FAO, 2015). Therefore, there has been a growing need for reliable biomass estimation approaches to understand the pools and fluxes of carbon from these forests towards the implementation of climate change mitigation policies such as REDD+ (IPCC, 2006).

Although different approaches have been developed to estimate the aboveground biomass of the forests, allometric equations are imperative and gaining wider recognition (Hossain *et al.*, 2023b; Henry *et al*., 2011; Chave *et al*., 2005). The destructive (i.e., direct) method of biomass estimation which involves tree felling, though more accurate, is often time-consuming, exorbitant, and hardly practical especially when large forest areas and several species are involved (Ganamé *et al*., 2021; Fayolle *et al.*, 2013; Sawadogo *et al*., 2010). Of recent, non-destructive techniques are increasingly being considered, such that allow tree or log-sectional biomass estimation without a complete tree destruction (Saha *et al.*, 2021; Aghimien *et al*., 2020; Ige, 2018).

Several allometric models have been developed for predicting aboveground biomass across the tropics, some of which are generic multi-species models (e.g., Feldpausch *et al*., 2012; Chave *et al*., 2005; Brown *et al*., 1997), in the Sub-Saharan African forests (Mensah *et al*., 2017; Henry *et al*., 2011), in the West African region (Ganamé *et al*., 2021; Sawadogo *et al*., 2010; Aabeyir *et al*., 2020), and even in Nigeria (Aghimien *et al*., 2020; Ojo *et al*., 2020; Jibrin and Abdulkadir, 2015; Onyekwelu, 2014). However, there is still a dearth of suitable allometric equations especially those that are species-specific and locally developed for Nigerian forests with fewer trees (Aghimien *et al*., 2020) and across Sub-Saharan Africa (Henry *et al*., 2011). This, therefore, limits the accuracy of aboveground biomass estimation, posing great uncertainties in carbon storage estimates and carbon market mechanisms (Sileshi *et al*., 2014).

In addition, the majority of the studies which have developed allometric equations for Nigerian forests are conducted on public forests such as Oluwa forest reserve (Onyekwelu, 2014), Kpashimi forest reserve (Jibrin and Abdulkadir, 2015), etc. Oftentimes, these models are specifically developed for plantation tree species with high economic values like *Tectona grandis* (Ojo *et al*., 2020), *Gmelina arborea* (Onyekwelu, 2014), *Khaya senegalensis* (Aghimien *et al*., 2020). However, only limited studies (e.g., Jibrin and Abdulkadir, 2015) have developed models for indigenous tree species of high abundance in secondary forests and are of considerable importance to local livelihoods. In the same vein, little or no consideration has been given to the carbon sequestration potential of and studies in private forest ecosystems. Meanwhile, private participation in forest establishment, carbon storage and associated carbon initiatives need to be encouraged in the country as private forests can contribute significantly to the global carbon cycle (Jimoh and Bada, 2001). This study, therefore, aimed at developing species-specific aboveground biomass models for two dominant (native) species as well as all species combined for mixed-species stands in a private semi-natural forest estate in Nigeria.

MATERIALS AND METHODS

Study area

This study was carried out at Abayomi Farm Estate (AFE) Emerald Forest Reserve situated at Abayomi Farm Settlement, Ikoyi-Osun, Osun State, Nigeria. It is a private forest reserve, owned by AFE Company since 2003, covering about 300 acres of pristine 'semi-natural' forest. It lies between latitudes 7º35ˈto 7°29ˈN and longitudes 4º14ˈto 4º12ˈE, with an average temperature of 24ºC. In addition, it experiences a humidity of about 88% with annual precipitation of around 1,400 mm. The secondary forest conservatory is situated on the confluence of the Aworin Osun and Akinrin streams that flow into the Osun River (Fig. 1), and it is nestled between Rocky Mountains with riverside forests that support the echo habitat of the river (C21st, 2015). The forest experiences a tropical climate with two distinct types of seasons: dry and rainy. The dry season between October and March is usually a period of minimal rainfall, while the rainy season starts around April. The vegetation of the reserve, which includes a large riparian forest, is rich and composed of diverse species of conserved woody trees many of which are indigenous and are scarce in the general market.

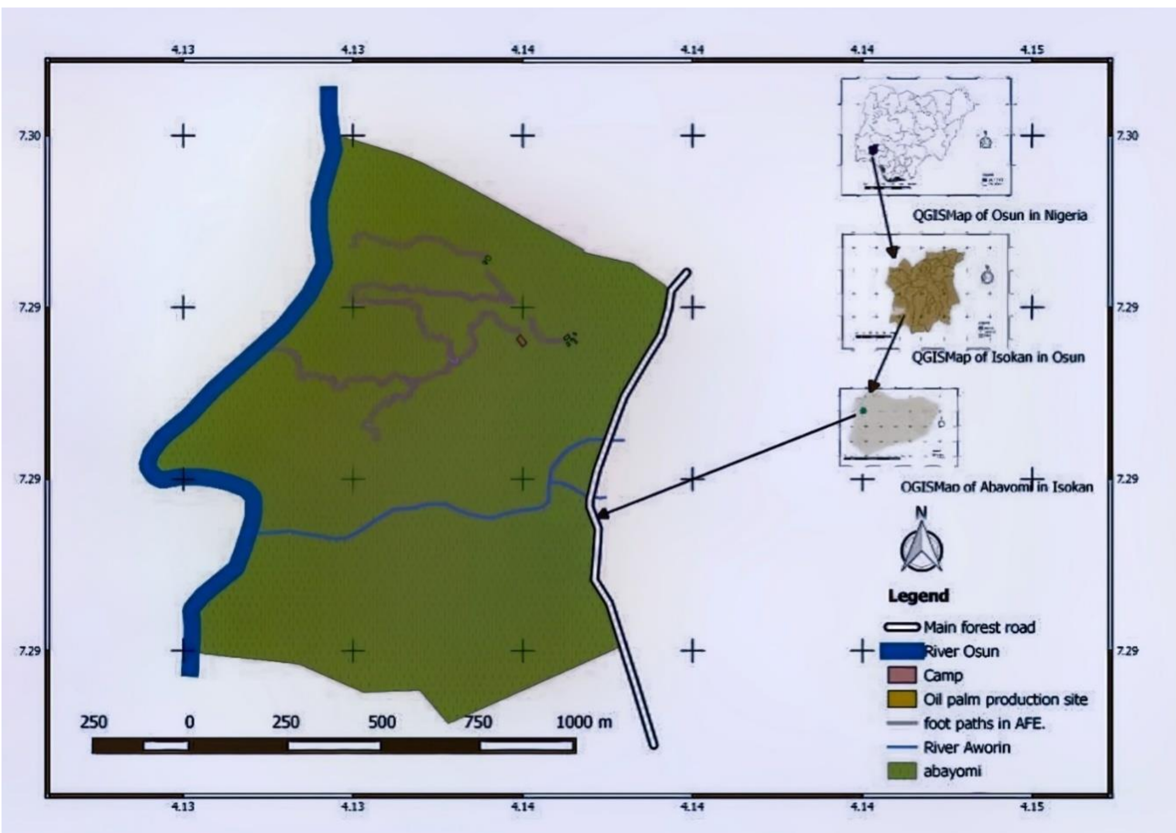

Figure 1. Map of AFE Emerald forest reserve

Data collection and analysis

Forest inventory-based approach was adopted to estimate aboveground tree biomass models in the study area, using a systematic line transect sampling technique. Two (2) transects of 200 m in length with a distance of 200 m apart were laid in the forest reserve. Two (2) Temporary Sample Plots (TSPs) of 50 m x 50 m in size were thereafter demarcated in alternate positions along each transect at 100m interval, totalling 4 sample plots. The tree parameters measured within the sample plots were diameters at breast height (DBH), at the base (Db), at the middle (Dm), and the top (Dt), as well as total height (H) using a diameter tape and a Spiegel relaskop appropriately. Meanwhile, only trees with DBH ≥ 10.0 cm were enumerated, and the specific wood densities of the trees were manually obtained from the Global Wood Density (GWD) database (Zanne, 2009) and the National Forest (Carbon) Inventory database (FAO, 2020). A taxonomist did the identification of the trees by their scientific names.

$$V = \frac{\pi H}{24}(Db^2 + 4Dm^2 + Dt^2) \ldots\ldots\ldots \; [1]$$

$$Biomass = V * WD * BEF \quad \ldots\ldots\ldots \; [2]$$

Where *V* represents volume over bark (m^3); *H* is the tree height (m); *Db*, *Dm* and *Dt* represent diameters (m) at the base, middle and top, respectively; π is pi; WD is wood density ($kg.m^{-3}$); BEF is Biomass Expansion Factor; and Biomass is the aboveground tree biomass (kg). The wood densities of the main tree species (*Cola gigantea* and *Picralima nitida*) were 480 and 410 $kg.m^{-3}$, respectively. Biomass expansion factor (BEF) used was 1.69 (Hossain *et al.*, 2023b).

Development of allometric models

The ordinary least squares (OLS) technique was used to fit the biomass equations, including the species-specific models for the two dominant species and the mixed-species or pooled allometric models, following the common pantropical model template from Chave *et al*. (2014). This template is based on transformed logarithmic form which is used to reduce the heteroscedasticity and has been typically adopted in many other biomass models (Ganamé *et al*., 2021; Sawadogo *et al*., 2010). In addition to the above-presented models, we fitted two additional models for the mixed-species using the pooled data (i.e., all species combined):

$$ln(AGB) = b_0 + b_1 ln(DBH) + \varepsilon \ldots\ldots \; [3]$$

$$ln(AGB) = b_0 + b_1\, ln(DBH) + b_2\, ln(H) + \varepsilon \ldots [4]$$

$$\ln(AGB) = b_0 + b_1\, ln(DBH) + b_2\, ln(WD) + \varepsilon \;\ldots\ldots \; [5]$$

$$ln(AGB) = b_0 + b_1 ln(DBH) + b_2 ln(H) + b_3 ln(WD) + \varepsilon .. [6]$$

Where AGB is aboveground biomass (kg), DBH is the diameter at breast height (cm), H is tree height (m), WD is wood density ($g.cm^{-3}$), ln is the natural logarithm, and the values b_0, b_1, b_2 and b_3 are model parameters, ε is the error term: $\varepsilon \approx NID(0, \sigma^2)$. To account for back transformation error, each model was multiplied by a correction factor (CF) derived from its mean square error (MSE): CF = exp(MSE/2).

Above ground biomass estimation

In this study, biomass estimation was done via a non-destructive approach using the volume and density of the trees enumerated. The forest is a conservation semi-natural forest and destructive sampling was not possible. We considered modelling the biomass of the two most-dominant native tree species in the forest reserve – *Cola gigantea* and *Picralima nitida*, and for all tree species combined. We computed the tree volume using the Newton function for volume determination (equation 1) (Aghimien *et al*., 2020; Ojo *et al*., 2020; Ige, 2018). The volume computed was then converted to biomass by the wood density and an expansion factor (equation 2) following Pajtik et al. (2011).

Evaluation of the developed models

The evaluation of the models' performance was done based on residual plots and goodness of fit statistics comprising of adjusted coefficients of determination (Adj-R^2), root mean square error (RMSE) as well as the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Adj-R^2 measures a proportion of biomass variation explained by the model; RMSE represents the standard deviation of the differences between predicted and observed values (i.e., the residuals); while AIC and BIC both represent significant criteria for selection among a finite set of models (Oluwajuwon *et al.*, 2022; Ganamé *et al.*, 2021; Aghimien *et al.*, 2020). Those (species-specific and pooled models) with the lowest values of RMSE, AIC and BIC and correspondingly highest Adj-R^2 are more suitable for adoption (Oluwajuwon *et al.*, 2022; Hossain *et al.*, 2023b; Ganamé *et al.*, 2021), and would therefore be recommended for biomass estimation in the semi-natural forest reserve. The relative position of each biomass model with regard to the fit statistics was determined by relative rank (Poudel and Cao, 2013).

$$R_i = 1 + \frac{(m-1)(S_i - S_{min})}{S_{max} - S_{min}} \dots\dots\dots\dots [7]$$

Where:

R_i represents the relative rank of each biomass model i (i = 1, 2, …, m); m is the number of models, S_i is the evaluation statistic of model i; S_{min} and S_{max} represent minimum and maximum values of S_i, respectively. A relative rank is a real number with the least being the best. We summed the relative ranks for each biomass model across the four indices (RMSE, AIC, BIC and Adj-R^2). The relative rank-sum was then used to decide on the final models.

Since we do not have sufficient and independent data to validate the selected models, k-fold cross-validation was used to ascertain the predictive ability of the models (Sileshi, 2014; Ogana, 2020). The same goodness of fit statistics: RMSE, AIC, BIC and Adj-R^2 were used to assess the cross-validation results. All computations and statistical analyses were carried out in R (R Core Team, 2020).

RESULTS

Summary of tree parameters used for model development

Table 1 presents the parameters of the sampled trees used to develop the biomass models. The minimum and maximum DBH of the trees were 9.23 cm and 147.04 cm, respectively with a mean value of 34.96 cm, while the tree height ranged from 5.3 m – 46.0 m with a mean of 19.5 m. The mean, minimum and maximum volume computed were 2.29, 0.04 and 38.59 m^3, respectively. The observed aboveground tree biomass of the individual sampled trees was within a wide range from 31.24 kg to as high as 18.26 Mg. The average tree diameter and height of the two dominant species: *C. gigantea* and *P. nitida* were 22.58 cm and 41.76 cm, and 15.2 m and 19.7 m, respectively.

Table 1. Summary of parameters of the tree variables for the dominant species and all species

Parameter	Minimum	Maximum	Mean	Standard error
Dominant species		***Cola gigantea (n=23)***		
DBH (cm)	9.23	61.11	22.58	2.280
Height (m)	5.3	35.1	15.2	1.620
Volume (m^3)	0.04	3.59	0.59	0.166
Biomass (kg)	31.24	2911.25	477.51	134.791
		Picralima nitida (n=18)		
DBH (cm)	13.05	121.26	41.76	6.282
Height (m)	13.0	33.1	19.7	1.321
Volume (m^3)	0.20	21.26	2.76	1.226
Biomass (kg)	140.04	14729.62	1914.54	849.557
		All tree species (n=176)		
DBH (cm)	9.23	147.04	34.96	1.736
Height (m)	5.3	46.0	19.5	0.615
Volume (m^3)	0.04	38.59	2.29	0.337
Biomass (kg)	31.24	18262.13	1524.26	197.399

Species-specific allometric models to estimate the aboveground biomass of the dominant species

Two species-specific ln-transformed biomass models were developed for each of the two dominant species in the AFE Emerald forest reserve – *Cola gigantea* and *Picralima nitida* (Table 2). For *C. gigantea*, Model 1 with only DBH as the predictor had adj-R^2, RMSE, AIC and BIC 77.1%, 0.512, 40.52 and 43.92, respectively. On the other hand, the further integration of another predictor, tree height, into the model (Model 2) improved the biomass prediction, recording an adj-R^2 of 95.4%. Model 2 therefore had a smaller relative rank-sum compared to Model 1, hence considered as better than the latter. Similarly, the inclusion of tree height in Model 4 for *P. nitida* improved prediction, e.g., from 88.7% to 95.1% adj-R^2. The relative rank-sums of Model 3 and Model 4 were 8 and 4, respectively. Therefore, a more precise species-specific estimation of the aboveground forest biomass would be made using the two-predictor (*DBH-H*) allometric models, considering the dendrometric variation of tree bole biomass. The equal variances of the fitted models depicted in the residual plots (Fig. 2) further confirm their predicting validity.

Allometric models for all identified species combined

Four models were developed to estimate the aboveground biomass of the mixed-species forest from the pooled data of all species (Table 3). The predictor variables used were DBH (Model 5), DBH and H (Model 6), DBH and WD (Model 7), and a combination of all the three variables – DBH, WD and H (Model 8). Model 5 had an adj-R^2 value of 84.6%, RMSE value of 0.50, AIC value of 264.11, and BIC value of 273.62. The inclusion of another covariate i.e., height in Model 6 improved the performance of the biomass equation. Its adj-R^2 was slightly increased by 6.9%. The substitution of tree height with wood density in Model 7 enhanced biomass predictions relative to Model 5. However, of all the mixed-species models developed for the forest, Model 8 which integrates all the three predictors proved the best with a high adjusted R^2 (97.0%), and the very lowest RMSE, AIC and BIC. The general trend based on the relative rank-sum was Model 8 > Model 6 > Mode 7 > Model 5, with the greater than sign '>' indicating the degree of superiority. The residual plots of the models also showed no evidence of heteroscedasticity (Fig. 2). 5-fold cross-validation of the selected models: Models 2 for *C. gigantea*, Model 4 for *P. nitida* and Model 8 for all species-combined confirmed the high predicting accuracy of the model forms, having generally recorded low RMSE, AIC and BIC as well as high adjusted R^2 ranging from 95.1 - 97.1% (Table 4). Thus, the models are considered suitable and precise for biomass prediction.

Table 2. Fitted aboveground biomass models for *Cola gigantea* and *Picralima nitida*

Species	Model	Dependent variable	Independent variable	CF	Parameter estimates b_0	b_1	b_2	Adj-R^2	RMSE	AIC	BIC	Rrel. sum
C. gigantea	1	lnAGB	lnDBH	1.140	-1.536^{ns}	2.342***	-	0.771	0.512	40.520	43.927	8.00
	2#	lnAGB	lnDBH and lnH	1.025	-2.639***	1.713***	1.151***	0.954	0.223	4.026	8.748	4.00
P. nitida	3	lnAGB	lnDBH	1.066	-0.582^{ns}	2.043***	-	0.887	0.358	20.088	22.759	8.00
	4#	lnAGB	lnDBH and lnH	1.027	-3.233***	1.798***	1.198***	0.951	0.229	6.027	9.589	4.00

AGB: Aboveground biomass, ln: natural logarithm, DBH: Diameter at breast height, H: Tree height, Adjusted R^2: adjusted Coefficient of determination, RMSE: Root mean square error, BIC: Bayesian Information Criterion, AIC= Akaike Information Criterion, b_0, b_1, and b_2: regression coefficients, CF: correction factor, Rrel. sum: relative rank sum (the least indicates the best model), # indicates the selected best-fit model for each species, (***) significant at α = 0.001, (**) significant at α = 0.01, (ns) non-significant.

Table 3. Pooled species models fitted for the aboveground biomass

Model	Dependent variable	Independent variable	CF	Parameter estimates b_0	b_1	b_2	b_3	Adj-R^2	RMSE	AIC	BIC	Rrel. sum
5	lnAGB	lnDBH	1.135	-0.687**	2.110***	-		0.846	0.504	264.111	273.622	16.00
6	lnAGB	lnDBH and lnH	1.072	-2.210***	1.734***	0.969***	-	0.915	0.373	160.720	173.402	10.78
7	lnAGB	lnDBH and lnWD	1.101	-0.569**	2.264***	0.793***	-	0.883	0.438	216.864	229.546	13.45
8#	lnAGB	lnDBH, lnWD and lnH	1.025	-2.264***	1.873***	1.094***	0.969***	0.970	0.221	-21.675	-5.823	4.00

AGB: Aboveground biomass, ln: natural logarithm, DBH: Diameter at breast height, H: Tree height, WD: Wood density, Adjusted R^2: adjusted Coefficient of determination, RMSE: Root mean square error, BIC: Bayesian Information Criterion, AIC: Akaike Information Criterion, b_0, b_1, and b_2: regression coefficients, CF: correction factor, Rrel. sum: relative rank-sum (the least indicates the best model), # indicates the selected best-fit model for mixed species, (***) significant at α = 0.001, (**) significant at α = 0.01.

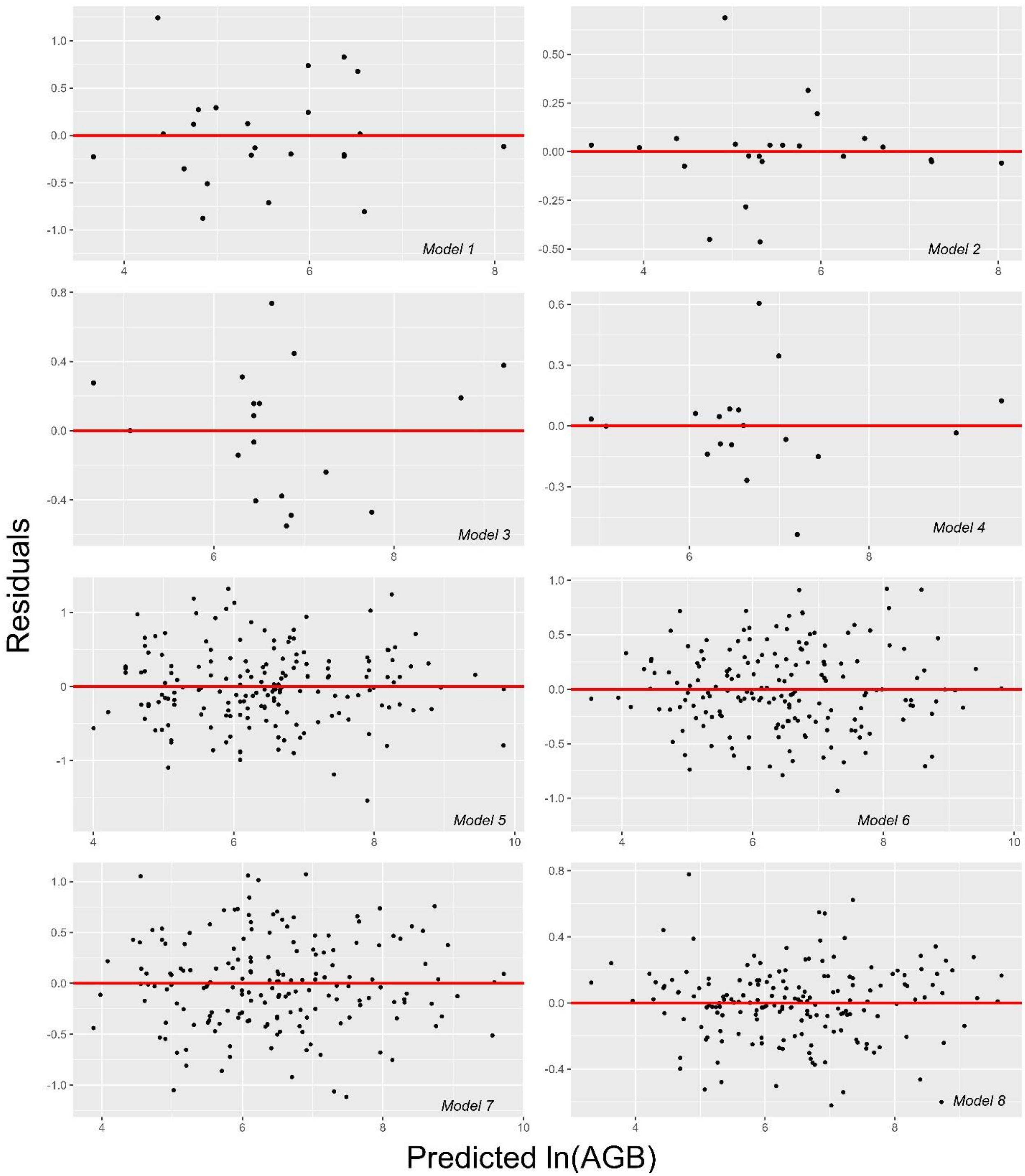

Figure 2: Residual plots of the models: Models 1 and 2 for *C. gigantea;* Models 3 and 4 for *P. nitida*; Models 5, 6, 7 and 8 for pooled species

Table 4: **5-fold Cross-validation of the selected models for the two dominant species and all species combined in the forest (spp. = 43, n = 176)**

Species	Model	RMSE	AIC	BIC	Adj-R^2
C. gigantea	2	0.229	-61.065	-56.523	0.954
P. nitida	4	0.264	-45.055	-41.493	0.951
All species	8	0.224	-521.142	-505.290	0.971

DISCUSSION

The carbon sequestration rate and potential of most of the forests in a typical developing tropical country like Nigeria have been significantly decimated over the years (Mitchard, 2018). Several deforestation and degradation activities are exasperatingly perpetuated in these forest estates. For instance, FAO (2015) reported Nigeria to have recorded the greatest net losses in forest area between 2010 and 2015 (410 K ha yr^{-1}), even though most of her forest reserves are public and decentralized – managed by the States' forestry departments – with supposed conservation mandates. Consequently, many of these forest carbon sinks have considerably become sources of carbon emissions (Oluwajuwon *et al.*, 2021; Oluwajuwon, 2021; Olorunfemi *et al*., 2019). However, private forestry is drawing global attention whereby landowners, encouraged by market-based instruments, do not only seek to invest in forest development for timber production but largely with the targets of enhancing the regulatory, supporting and cultural ecosystem services of their forest ecosystems, such as carbon sequestration (Wunder and Wertz-Kanounnikoff, 2009). AFE Emerald forest reserve is a notable example, as the management, though private, primarily aims at the conservation of forest biomass and resources for local sustainable livelihoods, biodiversity integrity, and other secondary functions like carbon/biomass storage.

We developed both species-specific and all species combined allometric equations to predict the aboveground biomass in the private semi-natural forest. Both sets of models were fitted using the linear (logarithmic) form. The use of ln-transformed models is important to stabilize the residual variance (homoscedasticity). A similar procedure has been widely used in other studies which estimated AGB accurately in tropical forests (Hossain *et al.*, 2023b; Ganamé *et al*., 2021; Mensah *et al*., 2017) and Nigeria (Aghimien *et al*., 2020; Jibrin and Abdulkadir, 2015). Meanwhile, Feldpausch *et al.* (2011) had asserted that the logarithmic models could be extrapolated with significant reliability, being attributed to the least deviation irrespective of the diameter class to which it is applied.

Amongst other tree parameters, DBH has been mostly used as the main, only, or best predictor variable in fitting allometric models for estimating woody tree biomass (Hossain *et al.*, 2023b; Henry *et al*., 2011; Basuki *et al*., 2009). Chave *et al*. (2005) asserted that one of the major reasons for this is that DBH accounts for about 95% of aboveground biomass. Meanwhile, it is generally known that the said parameter can be easily measured in forest inventories with higher accuracy than other dendrometric parameters coupled with its better availability in the forest inventory databases (Balima *et al*., 2020). Therefore, the models in this study were fitted principally with DBH. However, unlike studies like Basuki *et al.* (2009) where the DBH-only model proved more accurate in biomass estimation, the use of only DBH gave less reliable estimates for both tree species and, expectedly, in the pooled models in this study. In the case of the single-species models, the integration of the tree total height (H) as a secondary predictor variable improved the goodness-of-fit and performance of the model. Several authors have similarly reported that using multiple independent variables over DBH in biomass models is imperative to enhancing the accuracy of their estimations (Ganamé *et al*., 2021; Mensah *et al*., 2017; Feldpausch *et al.*, 2011) and their applicability to different sites (Ketterings *et al*., 2001).

The possible uncertainties that come with pantropical models in estimating species biomass of the forest estate could be alleviated using the mixed/pooled species models developed in this study, of which Model 8 – fitted with all the three independent variables (DBH, H, WD) – proved more reliable. This is evidenced by its significantly high adjusted R^2 and low RMSE, AIC and BIC. However, measuring these multiple variables in forest inventories might pose difficulty especially tree height. The much time and costs involved often encourage most forest management institutions and even researchers to conduct their inventory based on diameter, which is why Fayolle *et al.* (2013) recommended the use of DBH-only models for biomass estimation. In such scenarios, Model 7 which uses only DBH and WD could be adopted, as the specific wood densities can be obtained easily from online databases, although it is attributed to a slightly lesser accuracy than the *DBH-H* allometry. Meanwhile, some authors had demonstrated the importance of the information on wood density to biomass modelling and carbon estimation (Flores and Coomes, 2010; Chave *et al.*, 2005). This is often attributed to their variations per species and ignoring such in mixed-species models could affect the biomass prediction (Chave *et al.*, 2014). However, depending on the inventory situation, any of the models fitted in this study could be usable for estimating the biomass density in the semi-natural forest and others with similar site conditions, although the shortfall of the non-destructive method is linked to the limited enumeration the tree biomass volume along log sections.

CONCLUSION

Estimation of aboveground biomass and development of allometric equations is crucial in ascertaining the present and future situation of forest biomass for forest and carbon management. This study fitted models for assessing the aboveground biomass of the two dominant species (*Cola gigantea* and *Picralima nitida*) in the semi-natural Emerald rainforest in Nigeria, using the indirect "non-destructive" method. The species-specific and all species-combined allometric equations developed for the forest provided good estimates of aboveground tree biomass models generally with adjusted $R^2 > 85\%$, RMSE < 0.51, as well as low AIC and BIC values. However, the regression models with the additional predictor variable(s) like tree height and/or wood density to the fundamental DBH recorded higher prediction accuracy and performance, including Models 2, 4 and especially Model 8 which was fitted with all the predictors. They are therefore prescribed for reliable biomass estimation in the forest.

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