Websites:
http://www.sciencepub.net
http://www.sciencepub.net/researcher

Emails:
editor@sciencepub.net
marslandresearcher@gmail.com

Researcher

MARSLAND PRESS
Multidisciplinary Academic Journal Publisher

Modelling Carbon Stock In Sawn Logs Of Some Commercial Tree Species In Ilaobuachi Sawmill, Rivers State, Nigeria

Amadi Ihuoma, Eguakun Funmilayo Sarah, Oyebade, Bukola Amoo.

Department of Forestry and Wildlife Management, Faculty of Agriculture. University of Port Harcourt
funmilayo.popo-ola@uniport.edu.ng

Abstract: Forest management has both positive and negative varieties of effects on carbon stock. Carbon stock assessment is a basis for modelling carbon productivity in trees. This study develops models for predicting carbon stock of some commercial tree species in Ilaobuachi Sawmill, Rivers State, Nigeria. Data was obtained from sixteen commonly sawn log species with dbh ≥ 50cm base on their abundance. Correlation analysis was used to determine the degree of association between carbon stored and other measured variables. Different regression functions were used to develop the carbon stock model. Statistics such as Coefficient of determination (R^2), Root Mean Square Error (RMSE), Akaike Information Criterion (AIC) and Mean Absolute Percentage Error (MAPE) were used to test the accuracy of model. Five hundred and twenty eight logs of 16 species had diameter ranging from 0.71 cm to 1.10 cm. Basic wood density ranged from 0.39 cm^{-3} to 0.76 g cm^{-3} with an average of 0.54 g cm^{-3}. The logs had an average volume of 7.99 m^3 and carbon stock of 2.18 MgC. Diameter, volume, biomass had a strong positive relationship with carbon stored hence were good predictor of carbon stored. Among the regression functions tested, semi log function was selected as the best to predict carbon stored. Species that retain low amounts of carbon should be allowed to remain in the forest, thereby avoiding low sawmill yield hence fulfilling environmental functions. [Amadi I, Eguakun, F. S, Oyebade, B. A. **Modelling Carbon Stock In Sawn Logs Of Some Commercial Tree Species In Ilaobuachi Sawmill, Rivers State, Nigeria** ,*Researcher* 2023;15(7):29-37]. ISSN 1553-9865 (print); ISSN 2163-8950 (online). http://www.sciencepub.net/researcher. 04.doi:10.7537/marsrsj150723.04.

Keywords: Models, Sawn log, Timber, Sawmill, Carbon stock

1. Introduction

Globally, climate change is a problem that is already affecting biodiversity and the human economy. Although forest ecosystem helps to mitigate the effects of climate change, many people are dependent on forest resources for their subsistence.Forest resources offer the opportunity to harvest a variety of products, depending on timber quality and quantity, harvest economics, and market availability. Among these products are sawn logs for lumber or plywood, peeler logs for plywood, pulpwood, fuel wood, poles, piling, and posts. Harvesting and the use of harvested wood products play an important role in reducing carbon emissions along with good management for healthy forests (IPCC, 2001). However, the amount of carbon from a tree that is ultimately stored in wood product differs significantly depending on harvesting practices and stand characteristics. Sustainable forest management with accurate dimension of the carbon stock is essential to mitigate the greenhouse gas emissions that drive global climate change. Estimation of carbon stock at various scales requires application of methods that requires measure specific. These techniques can range from field inventories include field measurements, statistical model estimates, and physical model inversions based on field measured data.

One vital constituent of the global carbon cycle is the forest ecosystem which sequester atmospheric carbon dioxide (CO_2) by the process of photosynthesis (Harris *et al*., 2021; Nolan *et al*., 2021). According to the report of Pan *et al*. (2011), global forest ecosystems creates the largest carbon pool in the terrestrial biosphere and stores 861 ± 66 Pg carbon (C) with a sink rate of 2.4 ± 0.4 Pg C per year. Natural or anthropogenic occurrences such as wildfire and harvesting can directly remove the carbon from forest ecosystems (Seidl *et al*., 2014). Timber harvesting moves the carbon from forest ecosystems to sawn wood products (Brunet-Navarro *et al*., 2017; Zhang *et al*., 2020) which creates a carbon pool that can store the carbon for a long period and contribute to the mitigation of greenhouse effects (Gustavsson *et al*., 2006). Skog and Nicholson, (2000) stated that the carbon from forests which is moved to primary wood products such as lumber, pulp, and plywood are futher used in the manufacturing of wood in service (e.g., furniture, floor, and building).

Numerous approaches have been developed to quantify the carbon stored in sawn log, and they are different in their bulking allocation, industrial processes, carbon pools, and product removal (Brunet-Navarro *et al*., 2016). However, various factors including environmental change (Smith *et al*., 2020), technological advancement in the wood industry (*Li et al*., 2022), and plenty of socioeconomic factors (Zhang *et al*., 2020; Zhao *et al*., 2022) can affect the size of sawn log carbon pool. Literature that focuses on tree growth models which predict carbon stock yields of forests and carbon storage in timbers is becoming significant in quantitative forestry. According to Adesoye (2014), sustainable forest and forest resources management requires reliable estimates of growing stock because such information guides forest managers in timber evaluation. Estimation such as volume estimation is essential in sustainable forest management for accurate evaluations and for trading forest resources (Davis *et al*., 2001). Understanding the volume of wood in forests and the regions is fundamental for regional forest management planning, commercial harvest, and conservation. Volume estimates is also valuable in the modeling of carbon budgets.The roles of models in tree carbon stock estimation especially in tropical natural forest ecosystem cannot be overestimated.

Models are authentic tools for estimation of growing stock, timber valuation and allocation of forest areas for harvest which provides long-term decision-making and effective management strategies. The use of empirical models to predict tree growth as a function of tree attributes and plot or stand level variables are usually unbiased only in the range of data applied by volume, diameter at breast height (dbh), height, biomass, wood density which are able to quantify carbon storage (Avery & Burkhart, 2011). Allometric models make easy measurement of individual tree parameters using diameter at breast height (dbh) and total tree height (ht) from forest inventories to estimate volume and above ground volume biomass (Molto, Rossi & Blanc, 2013; Chave *et al.*, 2014). However, models developed by integrating theoretical information about the underlying relationships between dependent and independent variables are generally well specified and better reflect the fundamental biological and physical relationships shown by the system. These models can yield consistent results even when applied beyond the range of the data used to develop relationships between dependent and independent variables.

2. Material and Methods

Study Site

The study was carried out in Ilaobuchi Timber Sawmill Owners Association in Port Harcourt (latitude 4.51ºN, and longitude 7.01ºE), located in the south-south of Nigeria with temperatures averaging between 25°C and 28°C and an average rainfall of over 210mm up to 367mm, heaviest between June to October (NDES 2001). Most of the vegetation in the managed area consist of river, creeks, and estuaries, while stagnant swamps covers about 109 square kilometer (Km^2) with the area dotted with mangrove swamps are classified as "dense forest (Zabbey *et al*., 2004).

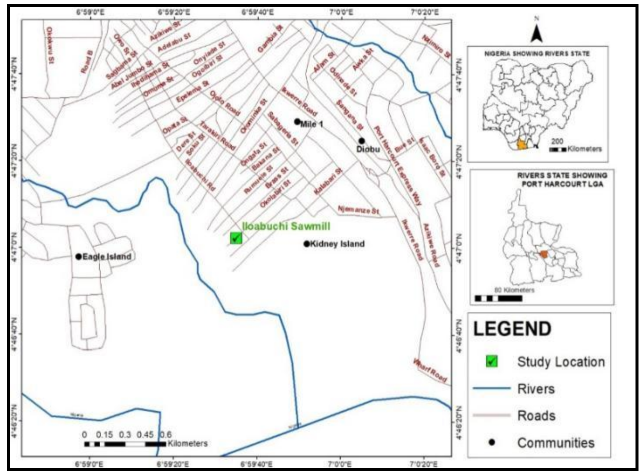

Fig 1: Map of Port Harcourt Showing study area

Sampling Techniques

Reconnaissance survey was carried out in order to identify and take inventory of the commonly sawn commercial trees species within the sawmill industry. The selection of sixteen (16) species was sampled. Total enumerations of logs in the selected species with size range of diameter ≥ 50 cm were measured. Philip (1994) method was used for the calculation of sample size. The number of individuals sampled was determined according to the sample size (n) for a population considered to be infinite using the formula;

$$n = \frac{t^2CV^2}{(E\%)} \quad \text{..........................(1)}$$

Where: n = optimal number of logs; t^2 = tabulated value of the Student's t-test (α = 0.05); cv^2 = coefficient variance; E^2 = permissible error limit (10%)

Data Collection

The following tree growth variables were measured for all selected trees species:

Diameter

$$D = \frac{C}{\pi} \quad \text{...(2)}$$

C= Circumference; π =3.142.

Volume of logs

$$V = (A_1 + A_2)/2) \times L \quad \text{..........................(3)}$$

Where; V = Volume of log in m^3; A_1 = cross-sectional area of the smaller end of log in m^2; A_2= cross sectional area of the large end of the log in m^2; L = length of the log in m using Smalian method (Kershaw *et al*., 2016).

Sawn wood product determination

The measurements were entered into a standardized field form where the quantities of the products (pieces) were assign in their dimensions: thickness (T;cm), width (W;cm), and length (L;m) base on categorized volume of lumber of each piece (VLum) using the formula*;*

$$Vlum = \sum(W * T * L)\ldots\ldots4$$

After determining the product volumes, they were added together by obtaining the volume of sawn wood for each processed log.

Wood basic density determination

For each section of logs, a wood disc was collected to determine the basic density of the wood and the carbon stored in sawn wood. The wood disks collected in the field were taken to the laboratory where a wedge is cut from each disk and submerged in water for 21 days. Then the immersion method was used to obtain the saturated volume of the wet wedges. Wedges were then oven dried at 70^{O} C for 48- 96 hours until weight stabilized. The basic wood density of each sample as the ratio of dry weight (g) to saturated volume (cm^3) was calculated (Wong, 2002). A density value for each individual tree were obtained as the arithmetic mean of the densities of the log segments from that individual, and a species mean was calculated as the average of the means for the individual trees.

Data analysis

Sawn log data were processed into suitable form for data analysis:

Biomass of logs computed as

B = Vlog× dbc ……………………….. (5)

Where: B = stem biomass of the sampled trees with bark (Mg), V log = volume of log with bark (m^3), and dbc= mean basic density of wood with bark (g cm^{-3}).

Biomass of sawn wood product computed as

Biomass =Vlum × dbc ………………….(6)

Where; dbc= the basic wood density, Vlum = the volume of sawn wood products.

Carbon Stock Estimation

The carbon stocks in the log and in the sawn wood product were calculated..The carbon stock were calculated by multiplying the biomass values by the mean carbon content of 0.49 with standard deviation 0.05 to obtain the carbon stock for each tree stem and sawn wood.

Carbon Stock in logs (CS)

CS = Biomass×0.49……………….. (7)

Carbon store in sawn wood product (FC_{sawn})

(FC_{sawn}) = Biomass×0.49 ………… (8)

Where: CS= carbon stock in logs; FC= Carbon stock in the sawn wood product.

Statistical Analysis

Descriptive statistics such as mean, regression and correlation analysis were used to summarize the estimated carbon stock parameters in sawn logs.

Model Development

The following model functions were tried:

Simple Linear models:

$Y = \beta_0 + \beta_1 X$……………………..**Eqn. 9**

Multiple Linear model:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$ ………………….**Eqn. 10**

Semi Logarithm model:

$\text{InY} = \beta_0 + \beta_1 X_1$…………………………**Eqn. 11**

Double Logarithms:

$\text{InY} = \beta_0 + \beta_1 \text{InX}_1$……………………………**Eqn. 12**

Quadratic function:

$Y = \beta_{0+}\ \beta_1 X_{1+}\ \beta_2 X_1^2$………………….**Eqn.13**

Cubic function:

$Y = \beta_{0+}\ \beta_1 X_1^2{}_+\ \beta_2 X_1^3$……………………...**Eqn.14**

Power function:

$Y = \beta_0 X_1^{\beta 1}$…………………………….**Eqn.15**

Exponential function:

$Y = \beta_0 e^{\beta 1 X}{}_1$…………………….........**Eqn.16**

Combine variables:

$Y = \beta_{0+}\ \beta_1 (X_1^2)\ X_2$………………...... **Eqn.17**

Inverse function:

$Y = \beta_{0-}\ \beta_1 X_1^{-1}$………………………… **Eqn.18**

X = Log variables such as dbh, Commercial length, Volume, Wood basic density (dbc), Biomass (B) and Carbon store in sawn wood product (FC); β_0, β_1 = model parameters

Models Assessment

Coefficient of Determination (R^2)

This is a measure of the proportion of variation in the dependent variable that is being explained by the behaviour of the independent variable. For the model to be accepted, the R^2must be high (at least,≥50%).

$$R^2 = 1 - \frac{SSE}{SST} \ldots\ldots Eqn.19$$

Where; SSE=error sum of squares, SST=total sum of squares.

Root Mean Square Error (RMSE): Represents the sample standard deviation of the differences between predicted and observed values. It estimates must be low as much as possible in order to reduce biased. The equation(s) with the highest R^2 and lowest RMSE were chosen and adjudged the best.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$ **…………..Eqn.20**

Akaike information criterion (AIC): It is a criterion for equation selection among a finite set of equations with the best fit; the model with the lowest AIC is preferred for model development (Akaike, 1974; Chave *et al*., 2005). The mathematical expression for comparing maximum likelihood equations is defined as:

$AIC = NIn(\sum_{i=1}^{n}(yi - \acute{y})2/n) + 2K$ ………***Eqn. 21***

Where: y_i = observed value; $\hat{y}_i$ = predicted value; N = number of observations; K = number of parameters estimated.

Mean Absolute Percentage Error (MAPE): It is also known as mean absolute percentage deviation and it is essentially used as a measure of prediction accuracy of a forecasting method (de Myttenaere, 2016). MAPE value of less than 10% shows that the model is highly accurate, 11–20% indicates a good model, while 21–50% suggests a reasonable model and more than 50% indicates inaccurate (Lewis, 1982).

MAPE= $1/n\sum_{i=1}^{n}\left(\gamma 1 - \frac{\gamma t}{\gamma 1}\right) \times 100$ **…..*Eqn. 22***

Where; $\gamma 1$ = observed value; γt= predicted value of the model

Model Validation

For model validation, data were divided into two sets (i.e. model-formulating set and model-validating set). The model formulating set was used for developing the models and the usefulness of the models were validated using the model validating set. The following statistics were then computed:

The student t-test

This was used to test for significant differences between the actual carbon in log values and the model outputs (predicted values) of the various models developed.

Bias

This was used to examine the absolute differences between the computed volumes and the model outputs, as:

$$Bias = \sum\frac{CSLog2 - CSLog1}{CSlog2}$$ **…………….Eqn.23**

Where; $CSlog_2$=actual (observed) carbon stock in logs, $CSlog_1$=predicted carbon stock in logs from the models.

3. Results

Characterization of Wood Species

The study sampled total of five hundred and twenty-eight (528) commercial valuable trees comprising. sixteen (16) identified species were selected being among the most commonly harvested from the forest area belonging to eleven (11) families. The highest were Fabaceae with (22.0%) followed by Rubiaceae (18.8%), Meliceae (14.4%), Malvaceae (9.5%), Apocynaceae (9.3%), Boraginaceae and Sterculiaceae (7.4%). Others had (3.4%, 3.0%) for Combretaceae and Ochnaceae. The least were Moraceae and Guttiferae (2.7, 2.3%) of the total number of families (Table 1).

Table 1. Composition of Wood species in the study area

Families	**Scientific Names**	**Local Names**	**F**	**%**
Apocynaceae	*Funtumia elastic*	Bush rubber	49	9.28
Boraginaceae	*Xylopiaaethiopica*	Uder	39	7.39
Combretaceae	*Terminalia ivorensis*	Black afar	18	3.41
Fabaceae	*Brachystegiaeurycoma*	Achi	14	2.65
	Pterocapuserinaceus	Kosso	50	9.47
	Pterocarpusosun	*boko*	26	4.92
	Petadethramacrophylla	Ugba	26	4.92
Malvaceae	*Ceibapentandra*	Silkcotton	50	9.47
Guttiferae	*Symphoniaglobulifera*	Okololo	12	2.27
Meliaceae	Khayaivorensis	Mahogany	29	5.49
	Berlinia grandiflora	ububa red	47	8.90
Moraceae	*Milicia excels*	Iroko	14	2.65
Ochnaceae	*Lophiraalata*	Ekki	16	3.03
Rubiaceae	*Mitragynacilitate*	Abura	49	9.28
	Naucleardiderrichii	Opepe	50	9.47
Sterculiaceae	*Mansoniaaltissima*	Mansonia	39	7.39
	Total		**528**	**100**

The diameter of sampled logs ranged from 0.71cm to 1,10cm with a mean volume of 7.99m^3 and biomass of 4.37Mg (table 2)

Relationship between carbon stocks in log with other parameters.

Correlation analysis was used to test the degree of association between the measured log attributes. There is significant relationship between carbon stock in log and all the growth parameters (diameter, length, volume, wood basic density (dbc), biomass and carbon stored in wood product; FC) as they produced a p-value less than 0.05. Positive correlation were observed in carbon stock in log with diameter (r =0.641), length (r =0.651), volume (r =0.818), wood basic density (r =0.816), biomass (r =1.000) and carbon stored in wood product (FC;r =0.622) .This result indicates that the carbon stock in log tend to increase with variables. (Table 3).

Carbon stock Model Development

Various model functions were tested and assessed for carbon stock in sawn log. The model assessment results and parameter estimates of the selected models for the tested function is presented in Table 4.. Volume and biomass were good predictor of carbon stored in sawn logs. The selected models had the highest R^2 and least MAPE & AIC respectively.

Model Validation

The results of model validation are presented in Table 5. The result revealed that in some of the developed models (Simple linear, double log and quadratic) there were no significant differences between the observed and predicted carbon stock. Hence these models are good for prediction purposes. However, the best model for current and future prediction is the semi log function with the highest R^2 and least MAPE value.

Table 2.Summary statistics of Wood variables used for modelling

Variables	**Min**	**Max.**	**Mean**	**Std.Error**	**Std. Dev.**
D(cm)	0.71	1.10	0.85	0.00	0.07
L(m)	3.51	4.27	3.68	0.01	0.18
Vol(m^3)	5.58	12.66	7.99	0.06	1.46
Biomass(Mg)	2.26	9.46	4.37	0.61	1.39
Dbc(g/cm^3)	0.39	0.76	0.54	0.00	0.10
FC(MgC)	0.08	13.66	8.79	0.07	1.68
CS(MgC)	1.13	4.73	2.18	0.03	0.70

CS=Carbon stock, D=Diameter , L= length, Vol=Volume, Dbc= Wood basic density and FC= Carbon stored in sawn wood

Table 3: Correlation matrix between Carbon stock of log (CS) and Parameters

	CS(MgC)	**Diameter(cm)**	**L(m)**	**V(m^3)**	**Dbc(g/cm^3)**	**B(Mg)**	**FC(MgC)**
CS(MgC)	1						
Diameter (cm)	0.641*	1					
L(m)	0.651*	0.275*	1				
V(m^3)	0.818*	0.860*	0.590*	1			
Dbc(g/cm^3)	0.816*	0.227*	0.426*	0.354*	1		
B(Mg)	1.000*	0.641*	0.651*	0.818*	0.816*	1	
FC(MgC)	0.622*	-0.032*	0.151*	0.182*	0.873*	0.622*	1

CS(MgC)- Carbon stock of log, Diameter (cm) , L(m)- Commercial length, V(m^3) – Volume of log,dbc(g/cm^3)- Wood basic density, B(mg)-Wood biomass and FC(MgC); Carbon stored in wood product (*≤ p-value 0.05).

Table 4. Sawn log carbon stock models

Function	Model Form	Model Statistics				
		R^2	RMSE	AIC	F-value	MAPE
Simple	$CS= \beta_{0+} \beta_1$ Vol	0.669	0.40	1.059e3	1.1e3*	16.36%
Multiple	$CS= \beta_{0+} \beta_1 L_+ \beta_3 Vol_+ \beta_4 Dbc$	0.988	0.07	981.42	1.5e4*	2.88%
Semi log	$InCS= \beta_{0+} \beta_1 D_+ \beta_2(L)_+ \beta_3 Vol_+ \beta_4 Dbc_+ \beta_5 B_+ \beta_1 FC$	0.997	0.00	984.54	2.8e4*	2.20%
Double log	$InCS= \beta_{0+} \beta_1 InDbc$	0.696	0.16	988.48	1.2e3*	21.77%
Quadratic	$InCS= \beta_{0+} \beta_1 D^2_+ \beta_2 FC^2$	0.893	0.10	981.34	2.193e3*	9.32%
Cubic	$InCS= \beta_{0+} \beta_1 B^2_+ \beta_2 B^3$	0.983	0.03	977.21	1.6e4*	6.35%
Power	$CS= \beta_0 Dbc^{\beta 1}$	0.696	0.16	1.059e3	1.20e3*	13.78%
Exponential	$CS= \beta_0^{\beta 1B}$	0.960	0.06	974.40	1.25e4*	49.83%
Combined variable	$InCS= \beta_{0+} \beta_1 (D^2)L_+ \beta_2 B$	0.960	0.06	978.26	6.248e3*	9.41%
Inverse	$CS= \beta_{0-} \beta_1 B^{-1}$	0.854	0.27	1.012e3	3.078e3*	9.44%

Table 5. Model Validation results

Model Forms	MOV	MPV	P-Value	Remark
Simple linear function	2.1831	2.1936	0.561	NS
Multiple linear function	2.1831	2.2266	0.020	S
Semi log linear function	0.7354	0.4718	0.063	NS
Double log function	0.7354	0.7523	0.374	NS
Quadratic function	0.7354	0.7567	0.355	NS
Cubic function	0.7354	0.7450	0.000	S
Power function	2.1524	1.9096	0.047	S
Exponential function	3.4263	1.3621	0.000	S
Combine variables function	0.7354	0.7504	0.00	S
Inverse function	2.1831	2.2316	0.000	S

Y= CS; Carbon stock, X_1 = D;Diameter, X_2 = L; length, X_3= V; Volm, X_4= dbc;Wood basic density, X_5= Biomass; X_6= FC; Carbon stored of wood product, MOV= Mean observed value, MVP= Mean predicted value; Parameters significant at (*≤ p-value 0.05),NS =Not significant; S=Significant

4. Discussions

The inventory of commonly sawn valuable species in course of this study in Ilaobuchi Sawmill of Port Harcourt shows the presence of different tree species. Fabaceae was the most abundant and Guttiferae the least. Fabaceae being the most diverse sawn families conforms to the report by Akinyemi and Oke (2014) that Fabaceae were one of the diverse families (in terms of species richness) present in the harvested forest. The reason for the poor establishments of some families in the area may be attributed to the effect of anthropogenic activities on growth and distribution of tree species may have played a role in the status of these species in the ecosystem, threatening the occurrence and development of certain species while favoring others. This is in line with Wardle *et al*. (2004) observations, that anthropogenic activities have great deleterious consequences on the abundance of tree species.

Wood resources constitute a significant element in the economic development. Despite its contribution to economic development, logging in the forests has been complicated as a result most abundant tree species in the tropical forests are harvested while others are abandoned and destroyed during harvesting (Arowosoge, 2010). Few species were commonly sawn in the study area include: *Mitragyna cilitate* (abura), *Brachystegia eurycoma* (achi*)*, *Lophira alata* (ekki), *Funtumia elastic* (bush rubber), *Ceiba pentandra (silkcotton/floater), Pterocarpus osun* (boko), *Milicia excels* (iroko), *Pterocapus erinaceus* (kosso), *Khaya ivorensis* (mahogany), *Mansoni aaltissima* (mansonia), *Berlinia grandiflora* (ububa red), *Symphonia globulifera* (okololo), *Nauclea diderrichii* (opepe), *Petadethra macrophylla* (ugba), *Xylopia aethiopica* (uder) and *Terminalia ivorensis* (black afara).The timber (logs) is characterized by abundance of wood with small diameter.. The possibilities are that most trees in the large diameter classes were constantly exploited, often times, illegally. This is similar to the finding of Jimoh *et al.* (2012).

Assessing carbon stock in logs provided a baseline for the monitoring and accounting support of carbon stock of sawn wood prediction in the study. Estimating carbon stock, it is important to include all structural variables that affect biomass in the model (Goodman *et al*., 2014, Silprandi *et al*., 2016), such as total height (reflected in commercial stem length) and basic wood density (Chave *et al*., 2014, Baker et al., 2004). Carbon stock assessment is a basis for modeling carbon productivity in logs. All the parameters in the tested models were significant at the 5% probability level. This is consistent with the findings demonstrated by Adekunle (2007) connections for most of the tree growth variables. Fitting of carbon stock in logs models were based on the total set. Before the models were developed correlation analysis were conducted to give the understanding of association between carbon stock in log and all the growth parameters (diameter, length, volume, wood basic density (dbc), biomass and carbon stored in wood product (FC). Carbon stored showed positive correlation with other measured variables. Biomass displays a higher relationship with carbon stock. The result aligns with the findings of Aigbe *et al.* (2012) which demonstrated that all the relationships among the tested parameters were positive indicating increase in value of one variable is associated with an increase in value of another variable.

Different models were examined for predicting carbon stock using simple linear function, multiple linear function, semi log function, double log function, quadratic function, cubic function, power function, exponential function, combine variables function and inverse variables function. All the tested functions fitted the data set. Aigbe and Ekpa (2015) findings on modelling tree volume in tropical rainforest revealed the use of double log function. Chave *et al*. (2014) observed quadratic and cubic regression function in performing better in their modelling The unique independent variable that features in all the models were diameter, volume, wood basic density and biomass proving these factors contributing to the carbon stock estimate. The statistics employed using R^2, RMSE, AIC and MAPE were good measure of overall predictive value of regression equations (Akaike, 1974; Chave *et al*., 2005; Adeyemi & Adesoye, 2010) particularly for this prediction suitable. A MAPE value of less than 10% shows that the model is highly accurate, 11–20% indicates a good model, while 21–50% suggests a reasonable model. This confirmation revealed that these selected models perform with low RMSE (%) and AIC with high R^2 values significant at probability level (0.005), thereby indicating that results obtained from these models above are of good quality.

All the model showed strong fit to carbon stock in log and the test of significance of carbon stock sampled showed no significant difference (*P*=0.05) between the observed value and the predicted values for simple, semi log, double log and quadratic model, hence are therefore suitable for current and future prediction of carbon stock in log among the logs within the range of data used in model development. Semi log function gave the best result hence was selected. One potential source of bias is the fact that this study only considered commercial tree species, while other equations consider all species.

5. Conclusion

Modelling provided a baseline for the monitoring and accounting support of carbon stock of log prediction hence, modelling is a useful contribution towards enabling improved and more confident decision making in management regarding buying, selling, and trading in forest resources. Wood resources requires a large amount of supporting information for sustainable management due to pressure mounted on them which has negatively impacted local species abundance. Growth parameters, especially diameter, volume, basic wood density, and biomass prove to be good predictors of carbon stock of logs. Semi log function was selected as the carbon stock in sawn logs predicting model.

Corresponding Author:
Dr. Eguakun Funmilayo Sarah
Department of Forestry and Wildlife Management
Faculty of Agriculture
University of Port Harcourt, Nigeria
Telephone: +2348038624661
E-mail: funmilayo.popo-ola@uniport.edu.ng

References

[1]. Adekunle, V. A. J. (2007). Non-Linear Regression Models for Timber Volume Estimation in Natural Forest Ecosystem,Southwest Nigeria. Research Journal of Forestry 1: 40-54

[2]. Adesoye, P. O. (2014). Canopy Layers Stratified Volume Equations for *Pinuscaribaea*Stands in SouthWest Nigeria using Linear Mixed Models. South-east European Forestry 5 (2): 153-161.

[3]. Adeyemi, A. A &Adesoye, P. O. (2010). Site Quality Assessment and Yield Models for *Tectona grandis*(Linn. F.) Stands in Ibadan Metropolis. Nigerian Journal of Forestry 40(2): 67-77

[4]. Aigbe, H. I., Modugu W. W., &Oyebade, B. A. (2012). Modeling Volume from Stump Diameter of *Terminalia Ivorensis*(A. Chev) in Sokponba Forest Reserve, Edo State, Nigeria. *ARPN JournalofAgriculture and Biological Science* 7 (3). 146-151

[5]. Aigbe, H.I., &Ekpa, N.E (2015).Modelling Tree Volume in Tropical rainforest of Afi River Forest Reserve in Cross River State, Nigeria. *International Journal of Scientific & Engineering Research*, 6.Retrived from http://www. ijser.org

[6]. Akinyemi, D.S., &Oke, S.O. (2014). Floristic composition and structural diversity of Shasha Reserve in Ile-Ife, Southwestern Nigeria. Not SciBiol 6(4): 433-440.

[7]. Arowosege O.G.E (2010). Lesser used wood species and their relevance to sustainability of tropical forests. In S.KoladeAdeyoju and S.O Bada (ed) Readings in Sustainable Tropical Forest Management pp. 305 – 32

[8]. Avery, T. E. & Burkhart, H. (2011). *Forest Measurements*, 5th edition. McGraw-Hill, NewYork

[9]. Baker, T.R., Phillips, O.L., Malhi, Y., Almeida, S., Arroyo, L., Di Fiore, A., Erwin, T., Killeen, T.J. &Laurance, W.F.. (2004). Variation in wood density determines spatial patterns in Amazonian forest biomass. *Global. Change. Biology*, 10, 545–562.

[10]. Brunet-Navarro, P., Jochheim, H., and Muys, B. (2016). Modelling carbon stocks and fluxes in the wood product sector: A comparative review. *Glob. Change Biol.* 22, 2555–2569. doi: 10.1111/gcb.13235

[11]. Brunet-Navarro, P., Jochheim, H., and Muys, B. (2017). The effect of increasing lifespan and recycling rate on carbon storage in wood products from theoretical model to application for the European wood sector. *Mitig. Adapt. Strateg. Glob. Change* 22, 1193–1205. doi: 10.1007/s11027-016-9722-z

[12]. Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure, J.-P., Nelson, B., Ogawa, H., Puig, H., Riéra, B., & Yamakura, T.(2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. In: *Oecologia*. 145: 87–99.

[13]. Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M.S., Delitti, W.B.C., Duque, A., Eid, T., Fearnside, P.M., & Goodman, R.C. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Glob. Chang. Biol*. **Vol** 20, 3177– 3190.

[14]. Davis, L.S., Johnson, K.N., Bettinger, P., & Howard, T.E. (2001). Forest management: To sustain ecological, economic, and social values (4th ed). Waveland Press, Inc., Long Grove, IL.

[15]. Goodman, R.C., Phillips, O.L., & Baker, T.R. (2014). The importance of crown dimensions to improve tropical tree biomass estimates. *Ecol. Appl*. 24, 680–698.

[16]. Gustavsson, L., Madlener, R., Hoen, H. F., Jungmeier, G., Karjalainen, T., Klöhn, S., et al. (2006). The role of wood material for greenhouse gas mitigation. *Mitig. Adapt. Strateg. Glob. Change* 11, 1097–1127. doi: 10.1007/s11027-006-9035-8

[17]. Harris, N. L., Gibbs, D. A., Baccini, A., Birdsey, R. A., De Bruin, S., Farina, M., et al. (2021). Global maps of twenty-first century forest carbon fluxes. *Nat. Clim. Change* 11, 234–240. doi: 10.1038/s41558-020-00976-6

[18]. Inter-governmental Panel on Climate Change. (2001). 'The Carbon Cycle and Atmospheric Carbon Dioxide', In: Houghton, J. T. et al. (eds.), *Climate Change 2001: The scientific Basis*, Cambridge University Press, Cambridge. 183– 237

[19]. Jimoh, S. O., Adesoye, P. O., Adeyemi, A. A &Ikyaagba, E. T. (2012). Forest Structure

Analysis in the Oban Division of Cross River National Park, Nigeria. Journal of Agricultural Science and Technology B2: 510-518.

[20]. Kershaw, J.A., Ducey, M.J., Beers, T.W., &Husch, B (2016). Forest Mensuration, (5th ed.). Wiley: Hoboken, NJ, USA,. 592.

[21]. Li, L., Wei, X., Zhao, J., Hayes, D., Daigneault, A., Weiskittel, A., et al. (2022). Technological advancement expands carbon storage in harvested wood products in Maine, USA. *Biomass Bioenergy* 161:106457. doi: 10.1016/j.biombioe.2022.106457

[22]. Molto, Q., Rossi, V., & Blanc, L. (2013). “Error propagation in biomass estimation in tropical forests,” *Methods in Ecology and Evolution*, 4 (2), 175–183, 2013.

[23]. NDES (2001).Biological Environment and Resources Report. RSUST, Port Harcourt 46. 251

[24]. Nolan, C. J., Field, C. B., and Mach, K. J. (2021). Constraints and enablers for increasing carbon storage in the terrestrial biosphere. *Nat. Rev. Earth Environ.* 2, 436–446. doi: 10.1038/s43017-021-00166-8

[25]. Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., et al. (2011). A large and persistent carbon sink in the world’s forests. *Science* 333, 988–993. doi: 10.1126/science.1201609

[26]. Philip, M.S. (1994). *Measuring Trees and Forests*. 2nd edition. Oxford: CABI Publishing. 310.

[27]. Seidl, R., Schelhaas, M. J., Rammer, W., and Verkerk, P. J. (2014). Increasing forest disturbances in Europe and their impact on carbon storage. *Nat. Clim. Change* 4, 806–810. doi: 10.1038/nclimate2318

[28]. Silprandi, N.C., Nogueira, E.M., Toledo, J.J., Fearnside, P.M., &Nascimento, H.E.M. (2016). Inter-site variation in allometry and wood density of GoupiaglabraAubl. in Amazonia. Braz. *Journal. Biol.*76, 268–276.

[29]. Skog, K. E., and Nicholson, G. A. (2000). “Carbon sequestration in wood and paper products,” in *The impact of climate change on America”s forests: A technical document supporting the 2000 USDA Forest Service RPA Assessment. Gen. Tech. Rep. RMRS-GTR-59*, eds L. A. Joyce and R. Birdsey (Fort Collins, CO: U.S. Department of Agriculture, Forest Service), 79–88.

[30]. Smith, M. N., Taylor, T. C., Van Haren, J., Rosolem, R., Restrepo-Coupe, N., Adams, J., et al. (2020). Empirical evidence for resilience of tropical forest photosynthesis in a warmer world. *Nat. Plants* 6, 1225–1230. doi: 10.1038/s41477-020-00780-2

[31]. Wardle, D. A., Walker, L. R. and Bardgett, R. D. (2004). Ecosystem Properties and Forest Decline in Contrasting Long- Term Chronosequence. Science 305: 509-513.

[32]. Wong, T.M. (2002).*A Dictionary of Malaysian Timbers.* Revised by Lim, S.C.& Chung, R.C.K. Malayan Forest Record; No. 30.Forest Research Institute Malaysia. Printed in Malaysia by Percetakan Haji Jantan, Kuala Lumpur, Malaysia..201.

[33]. Zabbey, N. (2004). Impacts of extractive industries on the biodiversity of the Niger Delta Region. Paper Presented At A 3-Day National Workshop on Coastal and Marine Biodiversity Management Holding in Pyramid Hotel, Calabar

[34]. Zhang, X., Chen, J., Dias, A. C., and Yang, H. (2020). Improving Carbon Stock Estimates for In-Use Harvested Wood Products by Linking Production and Consumption—A Global Case Study. *Environ. Sci. Technol.* 54, 2565–2574. doi: 10.1021/acs.est.9b05721

[35]. Zhao, J., Daigneault, A., and Weiskittel, A. (2022). Estimating regional timber supply and forest carbon sequestration under shared socioeconomic pathways: A case study of Maine, USA. *PLoSClim.*1:e0000018. doi: 10.1371/journal.pclm.0000018

7/5/2023