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

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**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 (R2), 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 m3 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/marsrsj15072](http://www.dx.doi.org/10.7537/marsrsj150723.04)3.04.

**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 (CO2) by the process of photosynthesis ([Harris *et al*., 2021](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B27); [Nolan *et al*., 2021](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B45)). According to the report of [Pan *et al*. (2011)](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B47), 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](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B54)). Timber harvesting moves the carbon from forest ecosystems to sawn wood products ([Brunet-Navarro *et al*., 2017](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B11); [Zhang *et a*l., 2020](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B70)) 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](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B26)). [Skog and Nicholson, (2000](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B57)) 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).

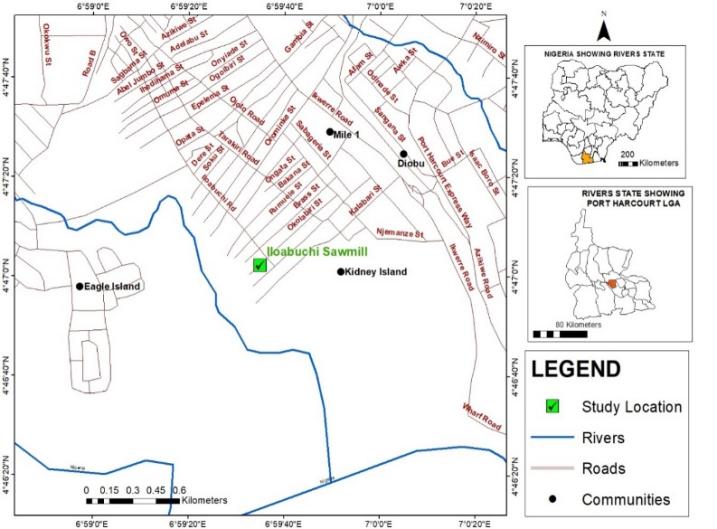
Numerous approaches have been developed to quantify the carbon stored in sawn log, and they are different in their bulking allocation, industrial processes, carbon pools, and product removal ([Brunet-Navarro *et al*., 2016](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B10)). However, various factors including environmental change ([Smith *et al*., 2020](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B59)), technological advancement in the wood industry ([*Li et al.*, 2022](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B37)), and plenty of socioeconomic factors ([Zhang *et al*., 2020](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B70); [Zhao *et al*., 2022](https://www.frontiersin.org/articles/10.3389/ffgc.2022.1055410/full#B72)) 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 (Km2 ) 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;

***……………………..(1)***

Where: n = optimal number of logs; t2 = tabulated value of the Student’s t-test (α = 0.05); cv2 = coefficient variance; E2 = permissible error limit (10%)

**Data Collection**

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

**Diameter**

***…………………………………… (2)***

C= Circumference;=3.142.

**Volume of logs**

***V = (A1+ A2) / 2) × L……………….…….. (3)***

Where; V = Volume of log in m3; A1 = cross-sectional area of the smaller end of log in m2; A2= cross sectional area of the large end of the log in m2; 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*;*

***……………………...4***

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 70O 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 (cm3) 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 (m3), 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 (FCsawn)***

***(FCsawn) = 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 = β0 + β1X……………………..**Eqn. 9**

Multiple Linear model:

Y = β0 + β1X1+ β2X2 ………………….**Eqn. 10**

Semi Logarithm model:

InY = β0 + β1X1………………………….**Eqn. 11**

Double Logarithms:

InY = β0 + β1InX1…………………………**….Eqn. 12**

Quadratic function:

Y= β0+ β1 X1+ β2X12………………….**Eqn.13**

Cubic function:

Y= β0+ β1X12+ β2X13……………………...**Eqn.14**

Power function:

Y= β0X1β1…………………………….**Eqn.15**

Exponential function:

Y= β0eβ1X1…………………….........**Eqn.16**

Combine variables:

Y= β0+ β1 (X12) X2………………....... **Eqn.17**

Inverse function:

Y = β0- β1 X1-1………………………… **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); β0, β1 = model parameters

**Models Assessment**

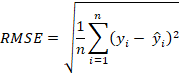
**Coefficient of Determination (R2)**

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 *R2*must be high (at least,≥50%).

***R2……………………….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 R2 and lowest RMSE were chosen and adjudged the best.

***…………..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 ═ …………****Eqn. 21***

Where: yi = observed value; ŷi = 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= …..Eqn. 22***

Where; = observed value; = 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:

***…………….Eqn.23***

Where; CSlog2=actual (observed) carbon stock in logs, CSlog1=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 7.99m3 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 R2 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 R2 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(m3) | 5.58 | 12.66 | 7.99 | 0.06 | 1.46 |
| Biomass(Mg) | 2.26 | 9.46 | 4.37 | 0.61 | 1.39 |
| Dbc(g/cm3) | 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(m3)** | **Dbc(g/cm3)** | **B(Mg)** | **FC(MgC)** |
| **CS(MgC)** | 1 |  |  |  |  |  |  |
| **Diameter**  **(cm)** | 0.641\* | 1 |  |  |  |  |  |
| **L(m)** | 0.651\* | 0.275\* | 1 |  |  |  |  |
| **V(m3)** | 0.818\* | 0.860\* | 0.590\* | 1 |  |  |  |
| **Dbc(g/cm3)** | 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(m3) – Volume of log,dbc(g/cm3)-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** | | | | |
| **R2** | **RMSE** | **AIC** | **F-value** | **MAPE** |
| Simple | CS= β0+ β1 Vol | 0.669 | 0.40 | 1.059e3 | 1.1e3\* | 16.36% |
| Multiple | CS= β0+ β1L + β3Vol + β4Dbc | 0.988 | 0.07 | 981.42 | 1.5e4\* | 2.88% |
| Semi log | InCS= β0+ β1 D +β2(L) +  β3Vol + β4Dbc + β5B+ β1 FC | 0.997 | 0.00 | 984.54 | 2.8e4\* | 2.20% |
| Double log | InCS= β0+ β1InDbc | 0.696 | 0.16 | 988.48 | 1.2e3\* | 21.77% |
| Quadratic | InCS= β0+ β1 D2+ β2FC2 | 0.893 | 0.10 | 981.34 | 2.193e3\* | 9.32% |
| Cubic | InCS= β0+ β1 B2+ β2B3 | 0.983 | 0.03 | 977.21 | 1.6e4\* | 6.35% |
| Power | CS= β0 Dbcβ1 | 0.696 | 0.16 | 1.059e3 | 1.20e3\* | 13.78% |
| Exponential | CS= β0β1B | 0.960 | 0.06 | 974.40 | 1.25e4\* | 49.83% |
| Combined variable | InCS= β0+ β1 (D2)L + β2B | 0.960 | 0.06 | 978.26 | 6.248e3\* | 9.41% |
| Inverse | CS= β0- β1 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, X1 = D;Diameter, X2 = L; length, X3= V; Volm, X4= dbc;Wood basic density, X5= Biomass; X6= 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 R2, 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 R2 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.

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