American Journal of Biological and Environmental Statistics
2022; 8(3): 81-92
http://www.sciencepublishinggroup.com/j/ajbes
doi: 10.11648/j.ajbes.20220803.15
ISSN: 2471-9765 (Print); ISSN: 2471-979X (Online)

On Carbon Sequestration Based on Above Ground Biomass (AGB) Modeling of Selected Tree Species in Nigeria

Oluwafemi Samuel Oyamakin, Peter Shina Adebayo

Biostatistics Unit, Department of Statistics, University of Ibadan, Ibadan, Nigeria

Email address:
fm_oyamakin@yahoo.com (O. S. Oyamakin)

To cite this article:
Oluwafemi Samuel Oyamakin, Peter Shina Adebayo. On Carbon Sequestration Based on Above Ground Biomass (AGB) Modeling of Selected Tree Species in Nigeria. *American Journal of Biological and Environmental Statistics*. Vol. 8, No. 3, 2022, pp. 81-92. doi: 10.11648/j.ajbes.20220803.15

Received: May 26, 2022; **Accepted**: July 4, 2022; **Published**: July 29, 2022

Abstract: Allometric models are important for quantifying biomass and carbon storage in terrestrial ecosystems. Generalized allometry exists for tropical trees but species- and site-specific models are more accurate. This paper is to investigate forest inventory data extracted from the Forestry Research Institute of Nigeria (FRIN) repository to compute the Above Ground Biomass (AGB) for five tree species namely; *Terminalia Superba, Bombax Rhodognaphadon, Gmelina Arborea, Mansonia Altissima, Pinus Caribaea, Khaya Senegalensis, Khaya Grandifoliola and Shorea Robusta*. Allometric models were used with the least squares' parameter estimates derived from the Marquardt algorithm to compute the above ground biomass of the five tree species selected. Descriptive Statistics alongside selected methods in inferential and non-parametric statistics such as Runs, Normality (KS & SW), and F-tests were done. Model selection criteria such as AIC, BIC, R^2, MSE, MAE and RSE were used to select the most appropriate models for modeling AGB of the selected tree species. Chave. Model (2005) fitted best the computed AGB for *Bombax Rhodognaphadon and Terminalia Superba* while Brown. Moist model (1989) fitted best the AGB of *Gmelina Arborea, Khaya Senegalensis, Khaya Grandifoliola and Mansonia Altissima.*

Keywords: Above Ground Biomass, Carbon Sequestration, Statistical Modeling, Non-linear Models, Allometric Models

1. Introduction

Accurate and precise information on the rates of change in forest resources is needed to ensure sustainable policies regarding the management and use of forests and trees. Estimates on the state and change of forest biomass must be stable in other to obtain valid resource forecasts and projections that will be suitable for planning purposes in Nigeria and all African countries in other to realize the Africa agenda for 2063. This is important to support the innovation that birthed the African Union strategy on Climate Change [1, 2], Land use [3, 4], and Challenges for a sustainable environment [5]. Biomass estimates for Nigeria's tropical forests are essential because of the rates at which the estimates are changing [13]. An increase in biomass and carbon content influences their role in the global carbon cycle thereby making the global tropical forests [10] have the greatest potential for mitigation of CO_2 through conservation and sustainable management of resources [12].

Anseeuw WL et al. [14] noted that the increase in commercial pressures on land and deepening of forest depletion as a result of deforestation has worsened global warming. Onoja AO et al. [15] indicated that deforestation in Nigeria has created environmental concern which is one of the most important issues of the last ten decades. Botkin and Keller [16] explained the relationship between deforestation and GHG emissions. He noted that when forests are cleared and the trees are burnt or rot, carbon is released as carbon dioxide which then increases the volume of greenhouse gas in the atmosphere that can combine with ozone in the ozone layer to deplete the protective layer of the atmosphere thus stepping up global warming. It was also established that over the past century human activities have been releasing GHGs at a rate unprecedented in geologic time. This has increased acceleration in the rate of emissions, the concentration of GHGs in the atmosphere by 30 percent, since pre-industrial times [22] and the Levels of Green House Gas (GHG) emission into the atmosphere which includes Carbon Dioxide (CO_2) levels have been associated with an increase in climate change. It is therefore believed that If humans continue to emit CO_2 at the current rate, all of these effects will excel and pose even greater threats to the present earth. Hence, this growing trend needs to be stopped using a step called Carbon sequestration [10].

Table 1. *Relative activity contribution to deforestation (Source: Porter and Brown (1996)).*

S/N	Activity	Contribution (%)
1	Commercial logging (selective and destructive)	20
2	Clearing for subsistence agriculture	50
3	Cattle ranching (Rangeland + pastoralism)	15
4	Others (construction of dams, roads, mining, plantations, etc)	5
5	Bush burning (forest fires)	10

Source: Porter and Brown (1996).

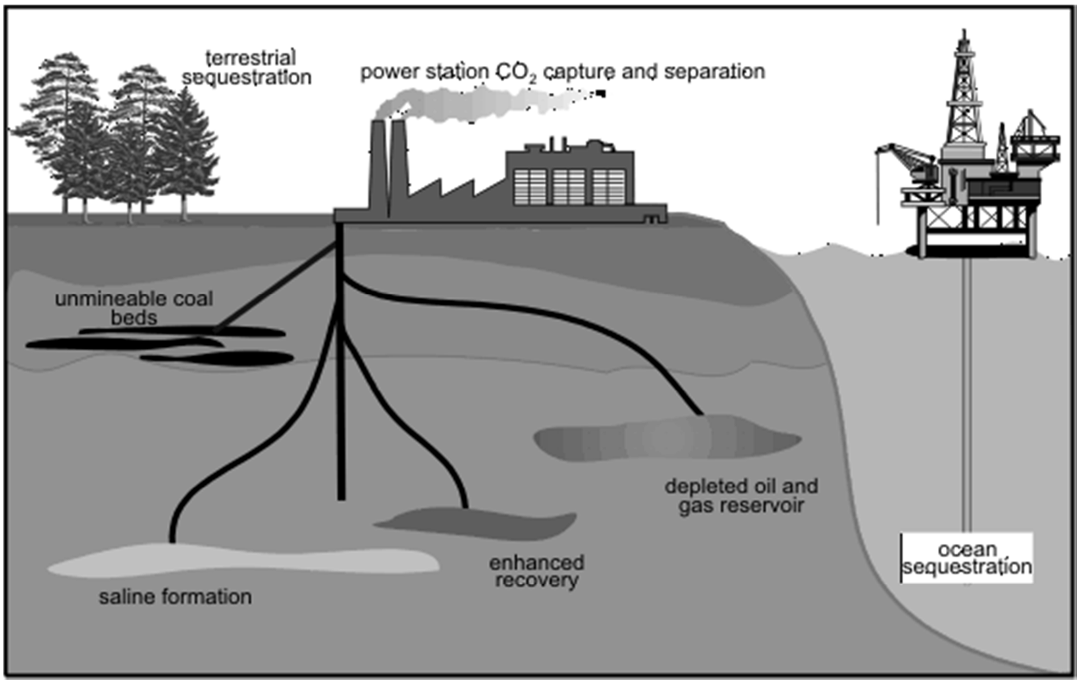

Figure 1. *Carbon Sequestration Process in the Nigeria Context.*

Table 2. *Common names and botanical names of some selected tree species.*

Botanical Name	Common Name	Family	Known Distribution in Africa	Uses	Air-Dry Wood Density (g/cm^3)
TERMINALIA SUPERBA	Afara	*(Combretaceae)*	Central African Rep., Drc	Plywood, Interior Use	0.45
BOMBAX RHODOGNAPHALON	Cotton wood Fleece-Fruit, N'ghuza	*(Bombacaceae)*	Nigeria, Kenya	Plywood, Blackboard, Boxes And Crates, Furniture	0.36
GMELINA ARBOREA	Yamane	*(Verbenaceae)*	Ivory Cost, Nigeria, Cameroon, Uganda, South Africa	Light Construction, Packaging, Furniture	0.41
MANSONIA ALTISSIMA	Ofun	*(Sterculiaceae)*	Nigeria, Central Africa Republic	High Class Joinery And Furniture	0.50-0.58
PINUS CARIBAEA	Pitch Pine (Softwood)	*(Pinaceae)*	Tropical Africa	General Utility Work	0.48
KHAYA SENEGALENSIS	Mahogany	*(Meliacea)*	Senegal, Egypt, South Africa	Utility And Decorative Work, Indoors And Outdoors, From Boatbuilding To Furniture And Joinery.	0.60
KHAYA GRANDIFOLIOLA	Broad Leaved Mahogany, Benin Mahogany	*(Meliacea)*	Guinea, Sudan, Uganda	Joinery, High Quality Furniture, Plywood	0.60
SHOREA ROBUSTA				All Types Of Joinery, Framing, Doors And Fittings. Also Used In Plywood	0.72

2. Methodology

Let $\{y_i, x_{i1},\dots,x_{ip}\}_{i=1}^{n}$ of *n* units be the datasets, and that the relationship between the dependent variable y_i and the *p*-vector of regressors x_i is linear. Then, through a *disturbance term* or *error variable* ε_i, this relationship can then be modeled. Thus, the model takes the form;

$$y_i = \beta_1 x_{i1} + \dots + \beta_p x_{ip} + \varepsilon_i = X_i^T\beta + \varepsilon_i, i = 1,\dots,n, \quad (1)$$

where ^{T} denotes the transpose so that $x_i^T\beta$ is the inner product between vectors x_i and β.

Often these *n* equations are stacked together and written in vector form as:

Where

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, X = \begin{pmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}. \quad (2)$$

Some remarks on terminology and general use:

1) y_i is called the *regressor and*, *endogenous variable*, *response variable*, *measured variable*, *criterion variable*, or *dependent variable*. The decision as to which variable in a data set is modelled as the dependent variable and which are modelled as the independent variables may be based on a presumption that the value of one of the variables is caused by, or directly influenced by the other variables. Alternatively, there may be an operational reason to model one of the variables in terms of the others, in which case there need be no presumption of causality.
2) $x_{i1}, x_{i2},\dots,x_{ip}$ are called *regressors*, *exogenous variables*, *explanatory variables*, *covariates*, *input variables*, *predictor variables*, or *independent variables*, but not to be confused with independent random variables. The matrix X is sometimes called the design matrix.
   a) Usually a constant is included as one of the regressors. For example we can take $x_{i1} = 1$ for $i = 1,\dots, n$. The corresponding element of β is called the *intercept*. Many statistical inference procedures for linear models require an intercept to be present, so it is often included even if theoretical considerations suggest that its value should be zero.
   b) Sometimes one of the regressors can be a non-linear function of another regressor or of the data, as in polynomial regression and segmented regression. The model remains linear as long as it is linear in the parameter vector β.
   c) The regressors x_{ij} may be viewed either as random variables, which we simply observe, or they can be considered as predetermined fixed values which we can choose. Both interpretations may be appropriate in different cases, and they generally lead to the same estimation procedures; however different approaches to asymptotic analysis are used in these two situations.
3) β is a *p*-dimensional *parameter vector*. Its elements are also called *effects*, or *regression coefficients*. Statistical estimation and inference in linear regression focuses on β. The elements of this parameter vector are interpreted as the partial derivatives of the dependent variable with respect to the various independent variables.
4) ε_i is called the *error term*, *disturbance term*, or *noise*. This variable captures all other factors which influence the dependent variable y_i other than the regressors x_i. The relationship between the error term and the regressors, for example whether they are correlated, is a crucial step in formulating a linear regression model, as it will determine the method to use for estimation.

In statistics, nonlinear regression is a form of regression analysis in which observational data are modelled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variables. The data are fitted by a method of successive approximations. The assumption underlying this procedure is that the model can be approximated by a linear function.

$$f(x_i, \beta) \approx f^0 + \sum_j J_{ij}\beta_j \quad (3)$$

$$J_{ij} = \frac{\partial f(x_i,\beta)}{\partial \beta_j} \quad (4)$$

Where

It follows from this that the least squares estimators are given by $\hat{\beta} \approx (J^TJ)^{-1}J^Ty$.

The nonlinear regression statistics are computed and used as in linear regression statistics, but using J in place of X in the formulas. The linear approximation introduces bias into the statistics. Therefore more caution than usual is required in interpreting statistics derived from a nonlinear model.

Non-linear least squares is the form of least squares analysis used to fit a set of m observations with a model that is non-linear in n unknown parameters (m > n). It is used in some forms of non-linear regression. The basis of the method is to approximate the model by a linear one and to refine the parameters by successive iterations. There are many similarities to linear least squares, but also some significant differences.

Consider a set of m data points, $(x_1, y_1), (x_2, y_2),\dots,(x_m, y_m)$, and a curve (model function) $y = (x, \beta)$, that in addition to the variable x also depends on n parameters, $\beta = (\beta_1, \beta_2,\dots,\beta_n)$, with $m \geq n$. It is desired to find the vector β of parameters such that the curve fits best the given data in the least squares sense, that is, the sum of squares.

$$S = \sum_{i=1}^{m} r_i^2 \tag{5}$$

is minimized, where the residuals (errors) r_i are given by

$$r_i = y_i - f(x_i, \beta) i = 1,2,\ldots,m. \tag{6}$$

The minimum value of S occurs when the gradient is zero. Since the model contains n parameters there are n gradient equations:

$$\frac{\partial S}{\partial \beta_j} = 2\sum_i r_i \frac{\partial r_i}{\partial \beta_j} = 0 \ (j = 1,\ldots,n) \tag{7}$$

In a non-linear system, the derivatives $\frac{\partial r_i}{\partial \beta_j}$ are functions of both the independent variable and the parameters, so these gradient equations do not have a closed solution. Instead, initial values must be chosen for the parameters. Then, the parameters are refined iteratively, that is, the values are obtained by successive approximation,

$$\beta_j \approx {\beta_j}^{K+1} = {\beta_j}^{K} + \Delta\beta_j \tag{8}$$

Here, k is an iteration number and the vector of increments, $\Delta\beta$ is known as the shift vector. At each iteration the model is linearized by approximation to a first-order Taylor series expansion about β^k

$$f(x_{i,} \beta) \approx f(x_{i,} \beta^k) + \sum_j \frac{\partial f(x_{i,} \beta^k)}{\partial \beta_j}(\beta_j - {\beta_j}^k) \approx f(x_{i,} \beta^k) + \sum_j J_{ij}\Delta\beta_j. \tag{9}$$

The Jacobian, J, is a function of constants, the independent variable *and* the parameters, so it changes from one iteration to the next. Thus, in terms of the linearized model,

$$\frac{\partial r_i}{\partial \beta_j} = -J_{ij} \tag{10}$$

and the residuals are given by

$$r_i = \Delta y_i - \sum_{s=1}^{n} J_{is}\ \Delta\beta_s;\ \Delta y_i = y_i - f(x_{i,} \beta^k) \tag{11}$$

Substituting these expressions into the gradient equations, they become.

$$-2\sum_{i=1}^{m} J_{ij} \left(\Delta y_i - \sum_{s=1}^{m} J_{is}\, \Delta\beta_s\right) = 0 \tag{12}$$

which, on rearrangement, become n simultaneous linear equations, the *normal equations.*

$$\sum_{i=1}^{m}\sum_{s=1}^{n} J_{ij} J_{is}\, \Delta\beta_s = \sum_{i=1}^{m} J_{ij}\ \Delta y_i \ (j = 1,\ldots,n) \tag{13}$$

The normal equations are written in matrix notation as

$$(J^T J)\, \Delta\beta = J^T \Delta y \tag{14}$$

When the observations are not equally reliable, a weighted sum of squares may be minimized,

$$S = \sum_{i=1}^{m} W_{ii} {r_i}^2 \tag{15}$$

Each element of the diagonal weight matrix W should, ideally, be equal to the reciprocal of the error variance of the measurement. The normal equations are then.

$$(J^T W J)\, \Delta\beta = J^T W\, \Delta y \tag{16}$$

These equations form the basis for the Gauss–Newton algorithm for a non-linear least squares problem.

2.1. Allometric Biomass Regression Equations

The Allometric Equations (AEs) are developed and applied to forest inventory data to assess the biomass and carbon stocks of forests. This made it the most widely used method for estimating biomass of forest. Generalised biomass prediction equations have been developed by researchers for different types of forest and tree species in other to obtain valid resource forecast and predictions [6-8, 11, 14-16]. AEs for biomass estimation were developed by establishing a relationship between the various physical parameters of the trees such as the diameter at breast height, height of the tree trunk, total height of the tree, crown diameter, tree species, etc. since incorporating more variables in the equations does not necessarily improve the accuracy of the estimate significantly; UNDP [17]. UNDP, Feng et al. and Vashum KT et al. [17-19] found that incorporating the height did not significantly improve the models based on dbh alone [19-21].

These equations are species specific, particularly in the tropics. The general equation has been developed in modified form. It is more general in [18, 22, 23] and applicable in field. It is not possible to cut all the trees to estimate their biomass. Considering the mathematical terms, the models are developed by [21, 28, 9, 20]. The model developed by [23, 29] to estimate above ground biomass has been used in present investigation. The literature revealed that this method is nondestructive and is most suitable method [18, 22-25].

The Brown [23] models require only dbh (cm) to predict total aboveground biomass (kg dry weight). However, the Chave [26] models require species-specific information on wood-specific gravity and provide a set of equations for each climatic zone that requires either dbh alone or both dbh and total tree height to predict total aboveground biomass. We used the wood densities of tropical tree species by [22, 27] when estimating aboveground biomass with the Alves [23] *and* Chave [26] generalized models. The generalized allometric models used in predicting total aboveground biomass (kg dry weight) of individual trees are listed below;

$$Y = \exp.\ \{-2.4090 + 0.9522 \ln (D^2 \times H \times \rho)\} \tag{17}$$

Brown Moist:

$$Y = \exp.\ \{-2.134 + 2.530 \times \ln(D)\} \tag{18}$$

Brown Wet:

$$Y = 21.297 - 6.953 \times D + 0.740 \times D^2 \quad (19)$$

Chave Moist:

$$Y = \rho \times \exp. \{(-1.499 + 2.148 \times \ln(D) + 0.207 \times (\ln(D))^2 - 0.0281 \times (\ln(D))^3\} \quad (20)$$

Chave Wet:

$$Y = \rho \times \exp. \{-1.239 + 1.980 \times \ln(D) + 0.207 \times (\ln(D))^2 - 0.0281 \times (\ln(D))^3\} \quad (21)$$

Where,
Exp. {....} means the "raised to the power of {....}".
Y = is the above-ground biomass (kg),
H = is the height of the trees (meter),
D = is the diameter at breast height (cm), and
ρ = is the wood density (gm/cm^3).
Wood densities were taken from the wood densities of tropical tree species [27].

2.2. Statistical Analyses

The Levenberg–Marquardt algorithm method of nonlinear regression techniques in SPSS was used to estimate the coefficient for the power function model in predicting the total aboveground biomass for the 8 selected tree species using the untransformed data and power function of the form:

$$Y = a X^b \quad (22)$$

Where;
Y = the dependent variable (e.g., aboveground biomass; kg dry weight),
X = the independent variable (dbh [cm]), and
a and b = are respectively, the scaling coefficient (or allometric constant) and scaling exponent derived from the regression fit to the empirical data.

Also, the coefficient of the combined allometric variable were estimated by the Levenberg–Marquardt algorithm method of nonlinear regression techniques in SPSS using the untransformed data and an exponential rise to a maximum function of the form:

$$Y = \exp. \{-a + b \ln(X_i^2 \text{ x } X_j \text{ x } c)\} \quad (23)$$

$$Y = \exp. \{-a + b \times \ln(X_i)\} \quad (24)$$

$$Y = a - b \times (X_i) + c \times (X_i^2) \quad (25)$$

$$Y = a \times \exp. \{(-b + c \times \ln(X_i) + d \times (\ln(X_i))^2 - e \times (\ln(X_i))^3\} \quad (26)$$

Where;
Y = the dependent variable (tree height (m)),
X_i and X_j = the independent variable dbh [cm] and h [m] respectively,
a, b, c, d and e = are respectively, the scaling coefficient and scaling exponent derived from the regression fit to the empirical data.

The weighing was necessary to remove heteroscedasticity in biomass data and to develop a biomass regression model of higher precision. Theoretically, weight should be inversely proportional to the variance of the residuals [28]. So, the residual errors were computed via the non-linear regression techniques in SPSS and the test for normality and randomness was carried out.

A number of statistics have been mentioned by [29] for evaluating goodness-of-fit and for use in comparing alternative biomass models. Among them the common ones are coefficient of determination (R^2), standard error of estimate (Se), mean square error (MSE), coefficient of variation (CV), Akaike information criterion (AIC), Bayesian information criterion (BIC), mean absolute error (MAE), and residual standard error (RSE).

Table 3. *Statistics used to compare the models.*

S.N.	Criteria	Formula	Remarks
1	R^2	$1 - \frac{RSS}{TSS}$ *RSS = residual sum of squares* *TSS = total sum of square*	RSS = $\sum_{i=1}^{n}(Y_i - \hat{Y})^2$ $TSS = \sum_{i=1}^{n}(Y_i - \bar{Y})^2$
2	MSE	$\sum_{i=1}^{n}(Y_i - \hat{Y})^2/n - k$	*n= number of sample size* *k= number of parameter*
3	MAE	$\sum_{i=1}^{n}\lvert Y_i - \hat{Y}\rvert/n$	$\hat{Y}$ *= is the estimated value of biomass by the model*
4	Se	$\sqrt{MSE}$	MSE = *mean square error*
5	CV	$(Se/\bar{Y})$	$\bar{Y}$ *is the arithmetic mean of observed biomass value*
6	RSE	$\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y})^2}{n-2}}$	RSE = *Residual standard error* Y_i *= observe value of biomass*
7	AIC	$n\ln\left(\frac{SSE}{n}\right) + 2k$	SSE = *Sum of square error*
8	BIC	$n\ln\left(\frac{SSE}{n}\right) + k\ln(n)$	

Goodness of fit for all regression equations was determined by examining *P*-values, the mean square of the error (MSE), the coefficient of determination (R^2), the coefficient of variation (CV), and by plotting the residuals (observed minus predicted values) against dbh. R^2 was calculated as 1 minus the sum of squares of the residuals (SSR) divided by the total sum of squares of deviations from the overall mean (Corrected SST). The best-fit models were selected as having the highest R^2; the lowest *P*-value, MSE, and CV; and the least amount of bias for under or over prediction of biomass across the entire range of sizes.

2.3. Some Generalizations

a) 35% of the green mass of a tree is water so 65% is solid dry mass;
b) 50% of the dry mass of a tree is carbon;
c) 20% of tree biomass is below ground level in roots so a multiplication factor of 120% is used; and
d) To determine the equivalent amount of carbon dioxide, the carbon figure is multiplied by a factor of 3.67.

The root system weighs about 20% as much as the above-ground biomass of the tree.

Therefore, to determine the total green weight of a tree, multiply the above-ground biomass of the tree by 120%.

Amount of carbon per tree (kg) = Tree mass (kg of AGB) x 50% (carbon%)

CO_2 sequestered per tree (kg) = Tree mass (kg of AGB) x 65% (dry mass) x 50% (carbon%) x 3.67 x 120%

Example: For a 12 year old spotted gum tree weighing 600kg green, then the amount of CO_2 sequestered by the entire tree = 600kg x 65% x 50% x 3.67 x 120% = 859 kg CO_2 or 72 kg CO_2 /yr. Finally if you would like to know the CO_2 sequestered per tree per year you need to look at the CO_2 and divide it by the age of the tree.

CO_2 sequestered per tree per year (kg) = X / age of the tree (yrs)

A forest inventory data was collected from the forestry research institute of Nigeria (FRIN). The data collected were given in Table 8 different tree species and the sample sizes of each tree were of different sizes. The individual trees measurement variable was in Height (H) and Diameter at Breast Height (DBH). Also, the common names and botanical names of the tree species were validated by literature analysis.

3. Discussion of Results

Table 4. *Secondary data of trees by species, diameter and height range.*

S.N.	SPECIES	DBH range (cm)	Height range (m)	Sample Size
1	TERMINALIA SUPERBA	12 – 70	3.5 – 17.5	31
2	BOMBAX RHODOGNAPHALON	5.2 – 40	3.5 – 15.5	56
3	GMELINA ARBOREA	5 – 49.3	6 – 24	31
4	MANSONIA ALTISSIMA	4.5 – 17.5	4.5 – 14	14
5	PINUS CARIBAEA	10 – 22.8	9 – 20	31
6	KHAYA SENEGALENSIS	23 – 62	10 – 24	31
7	KHAYA GRANDIFOLIOLA	8.5 – 25	7.5 – 17	17
8	SHOREA ROBUSTA	5.5 – 17	5.5 – 14	27

Table 5. *Scientific names, use and specific wood density of the [8] selected tree species.*

Botanical Name	Common Name	Family	Known Distribution in Africa	Uses	Air-Dry Wood Density (g/cm^3)
TERMINALIA SUPERBA	Afara	*(Combretaceae)*	Central African Rep., Drc	Plywood, Interior Use	0.45
BOMBAX RHODOGNAPHALON	Cotton wood Fleece-Fruit, N'ghuza	*(Bombacaceae)*	Nigeria, Kenya	Plywood, Blackboard, Boxes And Crates, Furniture	0.36
GMELINA ARBOREA	Yamane	*(Verbenaceae)*	Ivory Cost, Nigeria, Cameroon, Uganda, South Africa	Light Construction, Packaging, Furniture	0.41
MANSONIA ALTISSIMA	Ofun	*(Sterculiaceae)*	Nigeria, Central Africa Republic	High Class Joinery And Furniture	0.50-0.58
PINUS CARIBAEA	Pitch Pine (Softwood)	*(Pinaceae)*	Tropical Africa	General Utility Work	0.48
KHAYA SENEGALENSIS	Mahogany	*(Meliacea)*	Senegal, Egypt, South Africa	Utility And Decorative Work, Indoors And Outdoors, From Boatbuilding To Furniture And Joinery.	0.60
KHAYA GRANDIFOLIOLA	Broad Leaved Mahogany, Benin Mahogany	*(Meliacea)*	Guinea, Sudan, Uganda	Joinery, High Quality Furniture, Plywood	0.60
SHOREA ROBUSTA				All Types Of Joinery, Framing, Doors And Fittings. Also Used In Plywood	0.72

Source: Wikipedia (2014), Gisel Reyes. - Wood Densities of Tropical Tree Species.

Table 6. *Scientific names, use and specific wood density of the [8] selected tree species.*

Botanical Name	Common Name	Family	Known Distribution in Africa	Uses	Air-Dry Wood Density (g/cm^3)
TERMINALIA SUPERBA	Afara	*(Combretaceae)*	Central African Rep., Drc	Plywood, Interior Use	0.45
BOMBAX RHODOGNAPHALON	Cotton wood Fleece-Fruit, N'ghuza	*(Bombacaceae)*	Nigeria, Kenya	Plywood, Blackboard, Boxes And Crates, Furniture	0.36
GMELINA ARBOREA	Yamane	*(Verbenaceae)*	Ivory Cost, Nigeria, Cameroon, Uganda, South Africa	Light Construction, Packaging, Furniture	0.41
MANSONIA ALTISSIMA	Ofun	*(Sterculiaceae)*	Nigeria, Central Africa Republic	High Class Joinery And Furniture	0.50-0.58
PINUS CARIBAEA	Pitch Pine (Softwood)	*(Pinaceae)*	Tropical Africa	General Utility Work	0.48
KHAYA SENEGALENSIS	Mahogany	*(Meliacea)*	Senegal, Egypt, South Africa	Utility And Decorative Work, Indoors And Outdoors, From Boatbuilding To Furniture And Joinery.	0.60
KHAYA GRANDIFOLIOLA	Broad Leaved Mahogany, Benin Mahogany	*(Meliacea)*	Guinea, Sudan, Uganda	Joinery, High Quality Furniture, Plywood	0.60
SHOREA ROBUSTA				All Types Of Joinery, Framing, Doors And Fittings. Also Used In Plywood	0.72

Source: Wikipedia (2014), Gisel Reyes. - Wood Densities of Tropical Tree Species.

Table 7. *Descriptive data of showing the average diameter at breast height (DBH) and height.*

S.N	SPECIES	Average Height (m)	Average DBH (cm)	Sample Size
1	BOMBAX R.	8.8	16.5	56
2	GMELINA A.	14.0	30.5	31
3	KHAYA G.	14.3	16.8	17
4	KHAYA S.	15.3	40.0	31
5	MANSONIA A.	10.7	11.7	14
6	PINUS C.	14.8	15.8	31
7	SHOREA R.	9.9	15.8	27
8	TERMINALIA S.	12.8	40.8	31
	TOTAL	100.7199452	188.047723	238

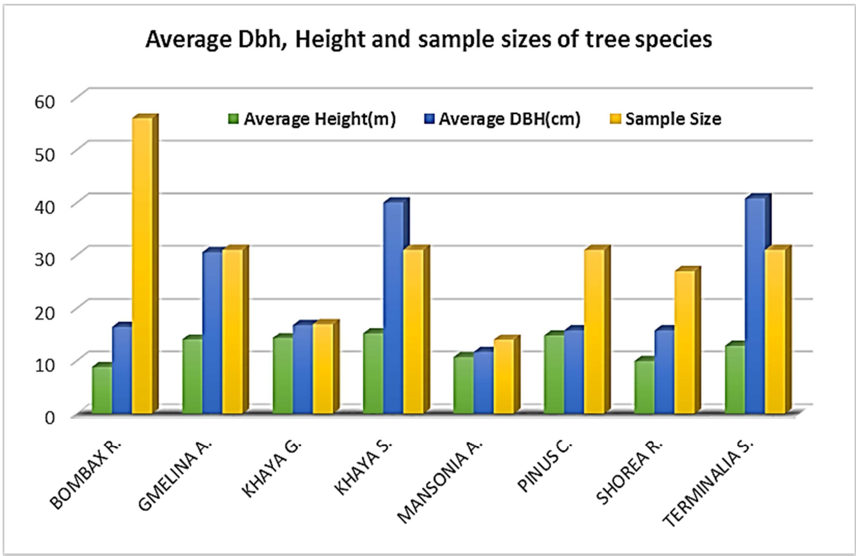

Figure 2. *Graph of descriptive analysis showing the average diameter at breast height (DBH) and height (H) including the sample sizes of the individual tree species.*

The chart in *Figure 2* shows that the tree species "Bombax" has the highest number of individual trees and the tree species "Terminalia Superba" is having the highest average DBH (cm) and lastly the tree species "Khaya Senegalensis" is having the highest average height H (m). Also, Table 6 shows that a total number of *238* trees was used in this study and the total average (H) and (DBH) was *100.7199452, 188.047723* respectively.

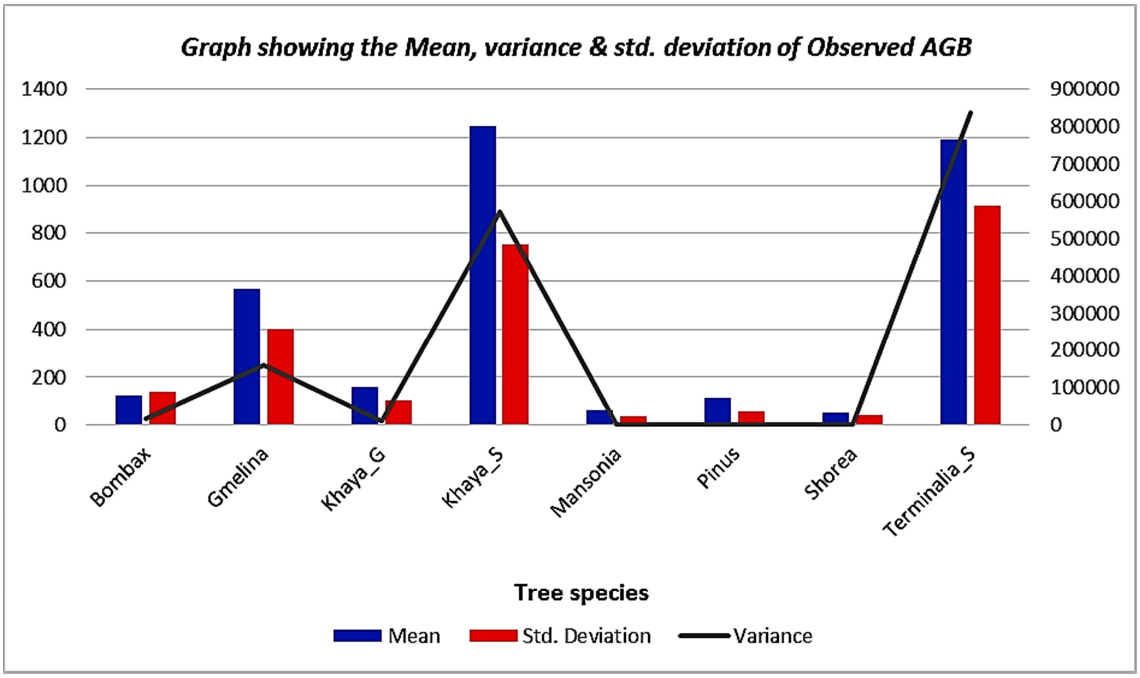

Figure 3. *Graph of descriptive analysis showing the mean, variance and standard deviation of the average observed AGB of the 8 selected tree species.*

The chart in *Figure 3* shows the trend or movement of the mean, std. deviation and variance of each of the tree species. It also reflects the tree species having the best average value to be GMELINA ARBOREA with value 566.51787. In Figure 3 above, the tree species with the lowest variance was *"MANSONIA ALTISSIMA"*, *"PINUS CARIBAEA"* followed by *"SHOREA ROBUSTA"*. Also from the figure above, *"TERMINALIA SUPERBA" and "KHAYA SENEGALENSIS"* have a larger std. deviation reflecting that the values of their data set are far away from the mean, on average.

The chart in *Figure 4* measures the skewness of the observed AGB (i.e. how symmetric the values are) and also the kurtosis for the observed AGB. On the basis of skewness, all the 8 selected tree species were positively skewed i.e. they are skewed to the right but the best tree species with the highest skewness was *BOMBAX RHODOGNAPHALON* with value 3.232. Also, on the basis of kurtosis, the tree with a negative kurtosis were *GMELINA ARBOREA, KHAYA GRANDIFOLIA* and followed by *PINUS CARIBEAN.* This means that these 3 trees have a flatter distribution and the tree with the highest peaked kurtosis was *BOMBAX RHODOGNAPHALON* with value 14.091.

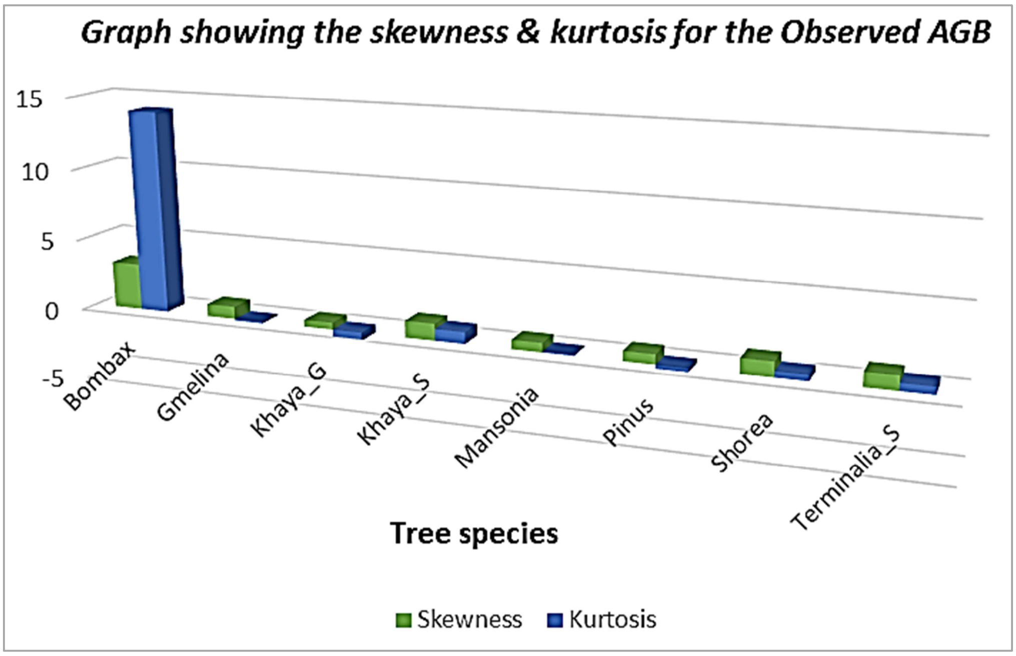

Figure 4. *Graph of descriptive analysis showing the skewness and kurtosis of the average observed AGB of the 8 selected tree species.*

Table 8. *Summary of the mean, std. deviation, variance, skewness, and kurtosis of the predicted AGB(s) for the eight tree species.*

Species	Descriptive					
	Model	**Mean**	**Std. Deviation**	**Variance**	**Skewness**	**Kurtosis**
BOMBAX	ALVES	122.0446	137.672855	18953.815	3.313	14.742
	CHAVE (moist & wet)	121.84679	139.719087	19521.423	3.233	14.102
	BROWN (moist)	122.28321	139.326423	19411.852	3.28	14.483
	BROWN (wet)	121.85393	139.672856	19508.507	3.146	13.231
	BASUKI	122.28321	139.326423	19411.852	3.28	14.483
GMELINA A.	ALVES	564.88677	377.724729	142675.971	0.732	0.072
	CHAVE (moist & wet)	566.26516	400.133027	160106.44	0.85	-0.157
	BROWN (moist)	567.19516	398.985792	159189.662	0.873	-0.126
	BROWN (wet)	566.51806	399.977266	159981.814	0.836	-0.223
	BASUKI	567.19516	398.985792	159189.662	0.873	-0.126
KHAYA G.	ALVES	160.51353	105.552325	11141.293	0.255	-1.019
	CHAVE (moist & wet)	161.86	104.706868	10963.528	0.472	-0.568
	BROWN (moist)	162.32824	103.911826	10797.668	0.54	-0.437
	BROWN (wet)	161.84824	104.726439	10967.627	0.472	-0.554
	BASUKI	162.32824	103.911826	10797.668	0.54	-0.437
KHAYA S.	ALVES	1253.3171	733.030407	537333.577	1.261	0.872
	CHAVE (moist & wet)	1249.64806	755.034732	570077.447	1.158	0.821
	BROWN (moist)	1249.46	755.342504	570542.298	1.156	0.85
	BROWN (wet)	1249.62387	755.055098	570108.201	1.152	0.796
	BASUKI	1249.46	755.342504	570542.298	1.156	0.85
MANISONIA	ALVES	61.78969	40.227211	1618.229	0.529	-0.359
	CHAVE (moist & wet)	61.99947	40.416661	1633.506	0.638	0.122
	BROWN (moist)	62.00802	40.401075	1632.247	0.649	0.199
	BROWN (wet)	61.99456	40.422154	1633.951	0.623	0.071
	BASUKI	62.00802	40.401075	1632.247	0.649	0.199
PINUS C.	ALVES	115.0771	56.16937	3154.998	0.743	-0.003
	CHAVE (moist & wet)	115.10871	58.627561	3437.191	0.686	-0.251
	BROWN (moist)	115.07742	58.710921	3446.972	0.664	-0.329
	BROWN (wet)	115.11323	58.63294	3437.822	0.67	-0.343
	BASUKI	115.07742	58.710921	3446.972	0.664	-0.329
SHOREA R.	ALVES	51.45222	42.554855	1810.916	0.842	-0.019
	CHAVE (moist & wet)	52.31296	41.637296	1733.664	1.034	-0.4
	BROWN (moist)	52.51222	41.365926	1711.14	1.093	0.573
	BROWN (wet)	52.32148	41.625893	1732.715	1.032	0.373
	BASUKI	52.51222	41.365926	1711.14	1.093	0.573
TERMINALIA S.	ALVES	1174.47742	928.339327	861813.905	0.842	0.289
	CHAVE (moist & wet)	1191.95935	915.346281	837858.815	0.986	0.499
	BROWN (moist)	1195.09258	911.117451	830135.009	1.025	0.607
	BROWN (wet)	1192.14645	915.136943	837475.625	0.972	0.425
	BASUKI	1195.09258	911.117451	830135.009	1.025	0.607

Table 8 gives a summary of the measure of central tendency and measure of shape carried out on the five predicted models of AGB for each of the tree species. It was seen that for *BOMBAX RHODOGNAPHALON* tree species, the mean of the five predicted models were unbiased as they gave similar mean value result and their variances and std. deviation gave a large value which signifies a large variation and deviation from the mean. Hence it was also observed that the five models were positively skewed to the right for the Bombax tree and the kurtosis value were very positively peaked.

On the basis of the mean, it was observed that the five predicted models were unbiased all through for all the 8 selected tree species but their std. deviation and variances were very large all through for all the 8 selected tree species.

On the basis of the skewness and kurtosis, the five predicted models for the 8 selected tree species were moderately positively skewed and peaked to the right except the kurtosis of ''GMELINA *ARBORE, KHAYA GRANDIFOLIA AND PINUS CARIBEAN''* that was negatively peaked. The parameter estimate based on the 5 allometric models used in this study was computed. The Levenberg–Marquardt algorithm method of nonlinear regression techniques in SPSS was used on the forest inventory data given. The equations considered were Alves. (1997) Chave. (2005), Brown. (1989) and Basuki. The models and their various characteristics are shown in *Table* 9 while the estimated parameters are tabulated in the *Table 10* below.

Table 9. *Summary of the allometric models and their various characteristics.*

Name of models	Equations
Alves (1977)	$Y = exp. \{-a + b\ ln(D^2\ x\ H\ x\ c)\}$
Brown (moist)	$Y = exp. \{-a + b \times ln(D)\}$
Brown (wet)	$Y = a - b \times (D) + c \times (D^2)$
Chave (moist & wet)	$Y = a \times exp. \{(-b + c \times ln(D) + d \times (ln(D))^2 - e \times (ln(D))^3\}$
Basuki	$Y = a\ D^b$

Where, Exp. {....} means the "raised to the power of {....}".
Y = is the above ground biomass (kg),
H = is the height of the trees (meter),
D = is the diameter at breast height (cm), and
a, b, c, d and e = are respectively, the scaling parameters.

The estimated parameters of *Table 10* below are species specific and these were the parameters used by the allometric biomass models to compute the Predicted AGB for all the 8 selected tree species.

Table 10. *Summary of the estimated parameter computed by the allometric model.*

Species	Parameters	ALVES	CHAVE (moist & wet)	BROWN (moist)	BROWN (wet)	BASUKI
Estimates						
	a	4.935	0.2668	2.456	45.822	0.086
	b	0.944	2.911	2.5	9.34	2.5
BOMBAX	c	9.623	4.02		0.738	
	d		-0.428			
	e		-0.04			
	a	7.302	0.01	1.899	39.141	0.15
	b	1.081	5.366	2.362	9.189	2.362
GMELINA A.	c	19.929	8.99		0.779	
	d		-1.8			
	e		-0.162			
	a	10.293	0.63	1.852	13.118	0.157
	b	1.187	2.075	2.412	5.436	2.412
KHAYA G.	c	88.106	2.354		0.783	
	d		0.279			
	e		0.061			
	a	2.979	2.18	2.068	414.055	0.126
	b	0.822	-10.177	2.466	34.805	2.466
KHAYA S.	c	8.175	-7.93		1.316	
	d		2.759			
	e		0.243			
	a	5.302	2.584	2.321	14.923	0.098
	b	0.983	0.7	2.561	5.477	2.561
MANISONIA	c	8.433	-0.813		0.75	
	d		1.448			
	e		0.204			
	a	6.568	0.031	2.107	40.086	0.122
	b	1.066	4.71	2.453	2.453	2.453
PINUS C.	c	10.432	9.245		0.786	
	d		-2.513			
	e		-0.308			
	a	7.164	0.286	2.207	13.907	0.11
	b	1.007	3.71	2.574	5.6156	2.574
SHOREA R.	c	46.466	5.457		0.835	
	d		-0.974			
	e		-0.105			
	a	6.62	0.013	1.967	145.294	0.14
	b	0.986	4.783	2.392	18.504	2.392
TERMINALIA S.	c	39.116	7.595		0.967	
	d		-1.248			
	e		-0.099			

4. Conclusion and Recommendations

In this study, the data covered a total number of 238 individual trees with a total average (height) and (Dbh) of *100.7199452* and *188.047723* respectively. The tree species with the highest number of trees (sample size) was *BOMBAX RHODOGNAPHALON* with 56 trees. Based on the average observed AGB, *KHAYA SENEGALENSIS'* has the highest mean value of 1249.62323 followed by *TERMINALIA SUPERBA* with mean value 1192.14716. This is due to the fact that the two tree species are affected by an outlier (i.e. extremely high numbers in the data set). Also *MANSONIA ALTISSIMA* gives the best reflection on the closeness and variation of the data set around the mean by having the lowest std. deviation of 40.458744 and variance 1636.910.

On the basis of skewness for the average observed AGB, all the 8 selected tree species were positively skewed i.e. they are skewed to the right but the best tree species with the highest skewness was *BOMBAX RHODOGNAPHALON* with value 3.232. Also on the basis of kurtosis for the average observed AGB, the trees with a negative kurtosis were *GMELINA ARBOREA, KHAYA GRANDIFOLIA* and followed by *PINUS CARIBEAN*. This means that these 3 trees have a flatter distribution and the tree that has the highest peaked kurtosis was *BOMBAX*

RHODOGNAPHALON with value 14.091.

From the computed estimates we gaves a summary of the measure of central tendency and measure of shape carried out on the five predicted models of AGB for each of the tree species. It was seen that for *BOMBAX RHODOGNAPHALON* tree species, the mean of the five predicted models were unbiased as they gave similar mean value result and their variances and std. deviation gave a large value which signifies a large variation and deviation from the mean. Hence it was also observed that the five models were positively skewed to the right for the Bombax tree and the kurtosis value were very positively peaked.

On the basis of the mean, it was observed that the five predicted models were unbiased all through for all the 8 selected tree species but their std. deviation and variances were very large all through for all the 8 selected tree species.

On the basis of the skewness and kurtosis, the five predicted models for the 8 selected tree species were moderately positively skewed and peaked to the right except the kurtosis of ''GMELINA *ARBORE, KHAYA GRANDIFOLIA AND PINUS CARIBEAN''* that was negatively peaked.

Using the least squares parameter estimates derived from the Marquardt algorithm, the best-fit models were selected by examining the mean square of the error (MSE), the coefficient of determination (R^2), the coefficient of variation (CV), standard error of estimate (Se), Akaike information criterion (AIC), Bayesian information criterion (BIC), mean absolute error (MAE), and residual standard error (RSE). The best-fit models were selected as having the highest R^2; the lowest MSE, AIC, BIC, MAE and CV; and the RSE which reflects the least amount of error that best describe the model of prediction of the AGB of the selected tree species.

For *''BOMBAX RHODOGNAPHALON''* the proposed best fit AGB models based on the (AIC, MSE, C.V, MAE and R^2) selection criteria with lowest AIC value of 132.7471211kg, lowest MSE value of 9.83kg, lowest C.V. value of 0.02572992kg, lowest MAE value of 2.078678571kg and the highest R^2 value of 0.999533253kg was the *Chave* (moist & wet) model.

For *''GMELINA ARBOREA''* the proposed best fit AGB models based on the (AIC, BIC, MSE, C.V) selection criteria was the *Brown 1989* (moist) model with the lowest AIC value of 179.3601702kg, lowest BIC value of 186.5301062kg, lowest MSE value of 281.216kg, lowest C.V. value of 0.029601002kg and on the basis of MAE selection criteria, Brown (wet) model has the lowest MAE value of 11.42812903kg. The *Chave* (moist & wet) model produced a higher R^2 value with 0.998479052kg showing the goodness of fit for the data of the model.

For *''Khaya Senegalensis''* tree species the proposed best fit AGB models was selected to be the *Brown 1989* (wet) model based on the (AIC, BIC, MSE, C.V) selection criteria with lowest AIC value of 44.25975014 kg, lowest BIC value of 48.42581687kg, lowest MSE value of 10.629kg, lowest C.V. value of 0.020143551kg and on the basis of MAE and R^2 selection criteria, *Chave 2005* model has the lowest MAE value of 2.159058824kg and highest R^2 value with 0.999273698kg showing the goodness of fit for the data of the model.

For *''Terminalia Superba.''* tree species the proposed best fit AGB models for the data was selected to be the *Chave 2005* (moist & wet) model based on the (AIC, BIC, MSE, C.V, and MAE) selection criteria with lowest AIC value of 185.8828857kg, lowest BIC value of 193.0528217kg, lowest MSE value of 347.072kg, lowest C.V value of 0.015627154kg and the lowest MAE value of 13.86877419kg. Also the *Chave 2005* (moist & wet) model produced an higher R^2 value with 0.999640912kg showing the goodness of fit for the data of the model.

In conclusion, the predicted allometric models presented in this study for quantifying the aboveground biomass of the eight selected tree species using the least squares parameter estimates derived from the Marquardt algorithm were discovered to be species-specific and should significantly improve capacity to accurately estimate biomass and carbon sequestration in Nigeria terrestrial ecosystems. In particular, the use of dbh as a sole predictor variable for all type of tree species will facilitate the use of inventory data to examine temporal and spatial variability in ecosystem structure and function. In addition, our parameter estimate can be used with the existing developed allometric biomass models in predicting the aboveground biomass of trees and wood formations. We recommend that AIC, BIC, MSE, MAE and RSE model criteria should be computed for any predicted AGB of so as to determine how appropriate the allometric models are for the given data of the tree species. However, care should be taken in the way human activities destroys, burn and cut down trees in Nigeria.

References

[1] IPCC Climate change 2007: impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; Cambridge university Press, Cambridge, United Kingdom and New York, NY, USA; 2007.

[2] World Bank the costs to developing countries of adapting to climate change new methods and estimate the global report of the economics of adaptation to climate change study consultation draft. Washington D. C.: The World Bank Group; 2010.

[3] TerrAfrica, Land & Climate: The role of sustainable land management (SLM) for climate change adaptation and mitigation in Sub-Saharan Africa (SSA); 2009.

[4] IPCC, Climate Change 2001: The Scientific Basic Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change, Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, Maskell K. and Johnson CA, Eds., Cambridge University Press, Cambridge, 2001; 881.

[5] Seo SN, Mendelsohn R, Dinar A, Hassan R, Kurukulasuriya. A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa. Environmental and Resource Economics. 2009; 43: 313-332.

[6] OECD Development Centre/African Development Bank. Growth trends and out look for Africa: Time to unleash Africa's huge energy potential against poverty concludes. African Economic Outlook; 2003-2004.

[7] Yohe GW, Lasco RD, Ahmad QK, Arnell NW, Cohen SJ, Hope C, Janetos AC, Perez RT. Perspectives on climate change and sustainability. Climate change 2007: Impacta, adaptation and vaulnerability, contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Parry ML, Canziani OF, Palutifok JP, van der Linden, PJ and Hanson CE, Eds., Cambridge University Press, Cambridge, UK, 2007; 811-841.

[8] Hoeller P, Dean A, Nicolaisen J. Macroeconomic implications of reducing greenhouse gas emissions: a survey of emprical studies. OECD Economic studies; 199. Retrieved on 17th July, 2012. Avalable: http://www.oecd.org/dataoecd/47/58/34281995.pdf

[9] FAO monitoring the interaction between agriculture and the environment: current status and future directions African commission on agricultural statistics 22nd session Addis Ababa, Ethopia, 30 November - 3 December, 2011. Retrieved on 23/6/2012. Available: http://faostat.fao.org.

[10] Dossou PJ. Evolution and impacts of coastal land use in Benin: The case of Seme-Podji commune. VADID contribution to ILC Collaborative Research Project on Commercial Pressures on Land, Rome: 2011.

[11] African Union Framework and guidelines on land policy in Africa: a framework to strengthen land rights, enhance productivity and secure livelihoods. African Development Bank/African Union/Economic Commission for Africa; 2009.

[12] Markelova H, Meinzen-Dick R. The importance of property rights in climate change mitigation. 2020 Vision Briefs 16 (10), International Food Policy Research Institute (IFPRI); 2009. British Journal of Environment & Climate Change, 4 (1): 83-94, 2014.

[13] Nordhaus WD. To slow or not to slow: the economics of the geeenhouse effect, revision of a paper presented to the 1989 meetings of the International Energy Workshop and the MIT Symposium on Envieonment and Energy; 1990.

[14] Anseeuw WL, Aiden W, Cotula L, Taylor M. Land rights and the rush for land: findings of the global commercial pressures on land research project. ILC, Rome; 2009. Retrieved on 20th May, 2012. Available: http://www.landcoalition.org/cplstudies.

[15] Onoja AO, Idaho C, Adah C. Policy implications of the effects of deforestation on Nigerian economy. Production and Agricultural Technology Journal, PAT. 2008; 4 (2): 114-120. Retrieved on 26th September, 2008. Available: http://www.patnsukjournal.com/currentissue

[16] Botkin DB, Keller EA. Environmental science: earth as a living plant. 2nd Ed. New York: John Wiley Press. 1997; 215.

[17] UNDP, Human Development Report 2007/2008. Fighting climate change; Human solidarity in a divided world, Palgrave Macmillan; 2007-2008.

[18] Feng, Kurkalova, Kling, and Gassman (Burtraw. 2003) Economic and Environmental Co-benefits of Carbon Sequestration inAgricultural Soils.

[19] Vashum KT, Jayakumar S (2012) Methods to Estimate Above-Ground Biomass and Carbon Stock in Natural Forests - A Review. J Ecosyst Ecogr 2: 116. doi: 10.4172/2157-7625.1000116.

[20] FAO, 1999, Above Ground Business Estimates at Saltonstall Ridge, East Haven, CT. 1999.

[21] FAO Corporate Document Repository (2009), Estimating biomass and biomass change in tropical forests. www.fao.org/documents/

[22] B. L. Chavan. Sequestered standing carbon stock in selective tree species grown in University campus at Aurangabad, Maharashtra, India., International Journal of Engineering Science and Technology Vol. 2 (7), 2010, 3003-3007.

[23] Litton. 2006. Allometric Models for Predicting Aboveground Biomass in Two Widespread Woody., the Journal of tropical biology and conservation/Biitropical 40 (3): 313-320 2008.

[24] Mani S, Parthasarthy N (2007) Above-ground biomass estimation in ten tropical dry evergreen forest sites of peninsular India. Biomass and Bioenergy 31: 284-290.

[25] Mohanraj R, Saravanan J, Dhanakumar S (2011) Carbon stock in Kolli forests, Eastern Ghats (India) with emphasis on aboveground biomass, litter, woody debris and soils. iForest 4: 61-65.

[26] Singh V, Tewari A, Kushwaha SPS, Dahwal VK (2011) Formulating ailometric equations for estimating biomass and carbon stock in small diameter trees. Forest Ecology and Management 216: 1945-1949.

[27] FAO, 1993. Forest resources assessment 1990 tropical countries. FAO Forestry Paper 112. Rome Italy.

[28] Brown S and A. E. Lugo, 1990. Tropical secondary forest. Journal of Tropical Ecology 6: 1-32.

[29] Brown S and A. E. Lugo, 1992. Above ground biomass estimates for tropical moist forests of the Brazillian Amazon, Interciencia 17: 8-18.