Journal of Forest Research
ISSN: 2168-9776
OPEN ACCESS Freely available online
Research Article

Bayesian Inference Procedure for Structural Characterization of Nigerian Tropical Forest

Sehinde Akinbiola[1*], Ayobami Salami[1,2], Olusegun Awotoye[3]

[1]Department of Sustainable Development, First Technical University, Ibadan, Oyo State, Nigeria;[2]Department of Space Application, Obafemi Awolowo University, Ile Ife, Osun State, Nigeria;[3]Department of Ecology and Environmental Studies, Obafemi Awolowo University, Ile Ife, Osun State, Nigeria

ABSTRACT

The complexity of the tropical forest structure remains a challenge in forest physiognomy assessment, which is a key indicator of forest productivity with implications on the carbon cycle, biodiversity, and ecosystem services. The study assessed structural characteristics, described variability within forest stands, and estimated carbon stocks, using simulation tools and tree modeling with a focus on understanding and quantifying ecological relationships. The study discovered a site-specific wood density difference of 0.07 g/cm^3 when compared with the generalized wood density for tropical forests by Food and Agricultural Organisation (FAO). Carbon stocks estimated with this site-specific wood density produced; 174 Mg Ca/ha^{-1}, 155 Mg Ca/ha^{-1} and 78 $MgCa/ha^{-1}$ respectively from three sampled Forest Reserves. Furthermore, the result showed that the most productive layers (emergent and canopy layers) of the forest clusters were predominantly hardwood species interspersed with softwood species with very large diameters. The height-diameter model indicated that although the height was a better predictor of the forest structural layer than the diameter, there was no clear margin for grouping species into layers in the region because of interspecies variations, temperature, and anthropogenic activities. The Bayesian Inference procedure provided a reliable approach for carbon stock estimate in the tropics with no legacy inventories.

Keywords: Forest structure; Carbon stocks; Bayesian inference procedure; Forestry

INTRODUCTION

The forest structure is critical to the forest ecosystem. The structure defines the complicated interactions between biotic and abiotic components forming broad ecological units as primary producers of biome [1]. Specifically, the quality and variability of forests are

Widely used as the environment and biological diversity measures [1-3], and the physiognomy directly impacts the type of biodiversity and genetic resources a forest supports [4]. Among the key functions of the structure is the regulation of the global carbon cycle by providing a robust carbon sink [5]. According to [6,7], the tropical structure is estimated to store more than 55% of the above-ground carbon stocks, therefore, the destruction and alteration of the forests contribute to the climate change phenomenon.

The consistent rise in carbon dioxide in the atmosphere and its effect on the environment have taken forest carbon accounting to the forefront of research and policy agendas [4,8-10], and consequently, several allometric models have been developed and their performance ensured extensive use for the estimation of carbon stocks in the tropics and pan tropics [11]. Nevertheless, carbon stock assessment methods are not completely developed and, more importantly, the uncertainty associated with carbon stock estimations is rarely assessed [6,9,12-14]. The Bayesian inference procedure offers a promising approach to these limitations [6,13]. Also, the height-diameter allometry, error propagations, and specific wood density of individual trees provide a reliable assessment of not only the above-ground biomass but other structural characteristics of the tropical forest [6,11,13,14].

The Nigerian tropical forest is in a dire state of decline [15-18], largely due to anthropogenic related activities that vary from overexploitation for timber, slash and burn farming to forest land conversion, resulting into large scale habitat destruction and biodiversity loss. Besides, the rise in population necessitates a stronger demand for raw materials utilization in developing countries like Nigeria that lack the infrastructural capacity required to successfully convert into a circular economy as in developed countries [16,19]. The continuous deforestation of the tropical forests extends into designated protected areas [20,21] and currently only a few patches of the once luxuriant pristine forest remain [16,22]. Previous studies in Nigeria use different types of allometric equations to convert forest inventories into carbon stock

Correspondence to: Sehinde Akinbiola, Department of Sustainable Development, First Technical University, Ibadan, Oyo State, Nigeria, E-mail: sehindeakinbiola@gmail.com

Received: 05-May-2022, Manuscript No. JFOR-22-17667; **Editor assigned:** 11-May-2022, PreQC No. JFOR-22-17667(PQ); **Reviewed:** 25-May-2022, QC No. JFOR-22-17667; **Revised:** 01-Jun-2022, Manuscript No. JFOR-22-17667(R); **Published:** 08-Jun-2022, DOI: 10.35248/2168-9776.22.11.329.

Citation: Akinbiola S, Salami A, Awotoye O (2022) Bayesian Inference Procedure for Structural Characterization of Nigerian Tropical Forest. J For Res. 11:329.

estimates [6,13,15-16,23,24]. The variation in the methodologies and allometry result in variations among estimates that are not the effect of nature. For instance, [6] used a derived model from the diameter at breast and height of tropical trees to determine carbon stocks in the tropical forests of Southwestern Nigeria [25]. Furthermore, [26] used a regression model derived from diameter at breast height to estimate carbon stock and wood density in a morphologically similar forest in Southwestern Nigeria. Errors that are often associated with this allometry are rarely calculated [6,13]. The Bayesian inference procedures take cognizance of error propagations in carbon stock assessment while generating uncertainty estimates through testing of different models based on root mean square errors. The research, therefore, used the Bayesian Inference Procedure [6], to calculate wood density, test height-diameter models, propagate errors, and estimate carbon stocks in the tropical forest of Southwestern Nigeria.

MATERIALS AND METHODS

Study area

The Omo–Shasha–Oluwa forest Complex lies within latitudes 7°1'7.67"N and 6°44'58.52"N, and longitudes 4°12'31.41"E and, 4°42'55.82"E (Figure 1). It has an estimated land area of 2,223 km^2 and a distance of about 25 km as the crow flies to the Atlantic Ocean from its southernmost boundary [19]. The forest reserves were created in 1925 and comprise clusters of contiguous forest reserves spanning parts of Ogun, Ondo, and Osun States. These reserves include the Omo, Oluwa, Shasha, Ife, and Ago-Owu Forest Reserves which in this study is regarded as the Omo-Oluwa-Shasha forest complex. Before the creation of the state administration in Nigeria, these five forest reserves were all part of the then Shasha Forest Reserve [20]. The pristine forest had experienced alteration of structure in some parts as early as 1966 when Gmelina arborea, Tectona grandis, and Pinus caribeae plantations were established in the forest reserves [27]. Recently, uncontrollable logging and slash and burn farming practices have further impacted the forest leaving it in a deplorable state [17,28].

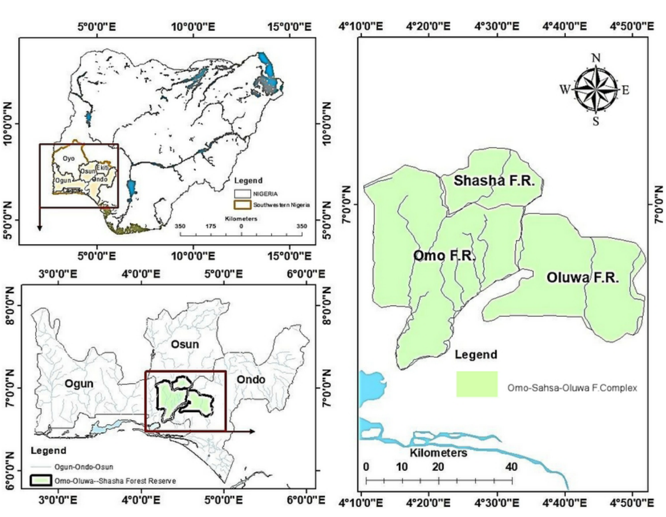

Figure 1: Map of the study area.

Sampling technique and biophysical parameters measurement

A stratified Random Sampling technique was used to select sampling plots. A sampling grid with 0.5 km by 0.5 km dimensions was overlaid on the land use land cover map derived from World View Imagery and 5 representative plots each for the vegetated land use classes were selected. Garmin 78 Hand Held GPS receiver was used to locate the center of the selected plots. The concentric plot assessment system (Figure 2) was used to select subplots [29]. Each modified plot was a cluster of four circular 17.95 m radius annular plots with one central 0.1 ha annular plot, three satellite 0.1 ha annular plots, four 7.32 m subplots, and one 2.77 m radius micro plot. Each modified plot also contained three 17.95 m long transects from the cluster center, with the first transect positioned at a random azimuth and the others at 60° and 120° from the first transect. Diameter at Breast Height (dbh), tree height, and species composition were measured for trees within the plots that were above 10 cm in diameter.

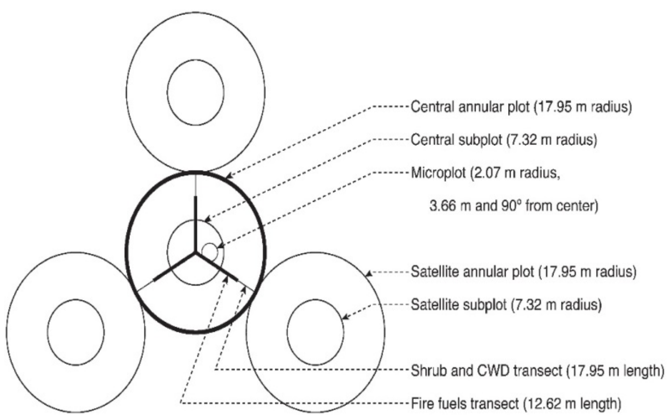

Figure 2: Field plot, adapted from (Gonzalez et al., 2010)

Bayesian inference procedure

The Bayesian Inference Procedure [6,7] designed with R statistical package was used to estimate above-ground carbon from the biophysical parameters collected in situ from the study area. The datasets were prepared in the Microsoft Office Excel Spreadsheet and then imported into R programming software.

Wood density: Wood density (WD) for the study area was calculated using the wood density function on the BIOMASS package. The function accessed the Global Wood Density Database (GWD) which provided the option to add generalized wood density values to undocumented species using the [6,30-32]. Before the wood density was calculated, the field data was subjected to taxonomic corrections using a function with a link to the online taxonomic database [33].

Tree- height allometry: The height-diameter allometry is important for the study area because of the closed canopy structure of the evergreen rainforest [6,11]. Specific height-diameter allometry was selected from the options of five models generated based on the Root Mean Square Errors (RMSE) which determines the suitability of the model for the study area [34,35].

Aboveground-biomass (AGB) calculation: The generalized equation was used to compute the AGB of each tree in Millgram after the wood density and height model were determined [6,11]. The equations are expressed below; Equation 1

$$\text{In(AGB)} = \alpha + \beta \text{In}(\rho \times D^2 \times \text{H}) + \varepsilon$$ ....[11] Equation (3)

Where α and β are model coefficient, is an error term. ρ [the random variables are identically distributed independently with the N (0, r 2)] distribution.

Equation 2

$$AGB_{est} = \exp\left[\partial/_2 + \alpha + \beta \ \text{In}\ (\rho\ \text{D}^2 H)\right] \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Equation 3

$$A = \text{In (H)} = \text{a} + \text{a}' \times E + b \times \text{In (D)} + \text{c} \times \text{In (D)}^2 + \varepsilon' \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

In previous studies, ln(H) was implicitly assumed to depend on ln(D). [23]

Equation 4

$$\text{AGB}_{est} = 0.0673 \times (\rho\ \text{D}^2 H)^{0.976}$$
$$(\sigma = 0.357, \text{AIC} = 3130, \text{df} = 4002) \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where D is in cm, H is in m, and is in g cm

Equation 5

$$\text{AGB}_{est} = 0.0559 \times (\rho\ \text{D}^2 H)$$
$$(\sigma = 0.361, \text{AIC} = 3211, \text{df} = 4003) \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Equation 6a

$In\ (H)$=0.893-E+0.760 $In\ (D)$-0.0340[In(D)]^2..................(8)

(AIC = 47, RSE = 0.243, df = 3998), where E is defined as

Equation 6b

E=(0.178 ×TS-0.938 ×CWD-6.61 ×PS)× 10 $^{-3}$ ....(9)

Equation 7

$$\text{AGB}_{est} = \exp\left[-1.803 - 0.976\text{E} + 0.976\ \text{In}\ (\rho) + 2.673\ \text{In (D)} - 0.0299\left[\text{In (D)}^2\right]\right] \ldots\ldots (10)$$

Equation 8

AGB=exp (-2.024-0.896.E+0.920.In(WD+2.795.In(D)-0.0461.[In(D)]^2...... (11)

Where the bioclimatic compound E is similar to that of [11].

According to [6], the last equation was necessary to correct errors in previous equations.

Error propagation: All the errors namely; Diameter Measurement Error (DME), Wood Density Error (WDE), Height Error (HE), and Allometric Model Error (AME) associated with AGB estimation are considered before the final error propagation. The errors were corrected using specialized arguments in the AGBMonteCarlo functions. The final propagation also used the AGBMonteCarlo rule where the procedure provided a distribution of the trees enumerated in the study area.

The final argument for propagating error in data sets of Omo -Sasha-Oluwa forest complex was;

AGBmc←AGBmonteCarlo (D=TropicalHD$D, WD=WDdatan$meanWD, H=Hlocals$H, errWD=WDdatan$sdWD, errH=Hlocals$RSE, Dpropag="chave2004")

Where AGBmc=(AGBMontearlo), D=Diameter at breast height of sampled trees, WD=Wood Density of the trees in the study area, H=selected H-Diameter allometry, errWD, errH and Dpropag are the arguments of all the errors associated with the estimation.

RESULTS

Wood density

A total of 16467 wood densities with 84 taxa were derived from all the sampled plots in the study area. The site-specific mean of the trees making up the structural network of the tropical forest of Southwestern Nigeria was 0.57 g/cm^3 belonging to three families and tree species namely; Fabacea (*Tetrapleura tetraptera*), Moraceae (*Milicia Excelsa*), and Meliaceae (*Entandrophragma cylindricum*) at Whereas the general wood density value for species-level had 91% while wood density to genus level had an 8% confidence level respectively. The lowest wood densities belonged to two species from two families which were; Annonaceae (*Cleistopholis patens*) and Malvaceae (*Bombax buonopozense*) with wood density values of 0.33 g/cm^3 and 0.32 g/cm^3 respectively. Furthermore, the highest density (0.92 g/cm^3) was recorded for *Klainedoxa gabonensis* , from the family of Irvingiaceae.

Height-diameter allometry

The height-diameter model of the study area (Table 1, Figures 3 and 4) indicated that Log 2 had the least RMSE (4.43) hence its selection to determine Aboveground-Biomass for the study area

Table 1: Compared height-diameter models showing distinguished colors, rmse and average biases of inventoried trees in the study area.

S/n	Model	Colour	RMSE	Average bias
1	Log 1	blue	4.6678	-0.0013
2	Log2	green	4.4328	2e-04
3	Log 3	red	4.4985	8e-04
4	Weibull	orange	5.8234	-0.0362
5	Michaelis- Menten	purple	5.3665	-0.0182

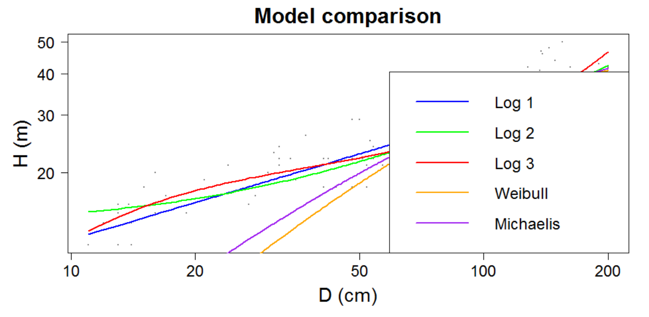

Figure 3: Height -diameter model of tree species in South-western Nigeria. Note: (———) Log 1, (———) Log 2, (———) Log 3, (———) Webull, () Michaelis.

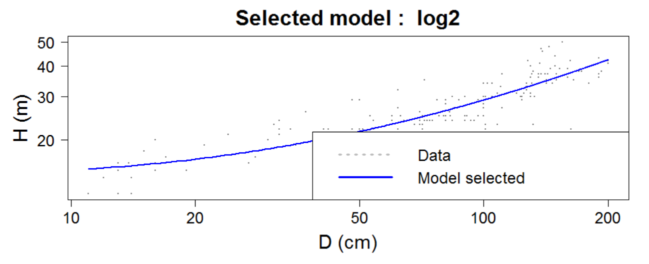

Figure 4: Selected Log 2 model from all allometry due to lowest RMSE. Note: (.......) Data, (———) Model selected.

Above-ground biomass and carbon stock estimates

The result Table 2 showed that Omo Forest Reserve sampled plot had the highest AGB and carbon stock (348.5 and 174 MgCa/ha^{-1})

while the least AGB and carbon stock from the three forest reserve sampled was Sasha Forest Reserve with (156 and 78 MgCa /ha^{-1}) respectively.

Table 2: Above-ground biomass in mg/m^2, and tonnes/ha^{-1} and Carbon stock estimates of the 1-hectare plot each for Omo, Sasha, and Oluwa forest reserves.

Forest reserve	AGB (Mg/m^2)	AGB estimates (MgCa/ha^{-1})	Carbon stock estimates (MgCa/ha^{-1})
Omo	348521558	348.5	174
Oluwa	310566394	310.6	155
Sasha	156650901	156.1	78

Note: 17.92 radius = 1009 m^2 .1 hectare=10,000 m^2. 0.1 hectare multiplied by 10=I hectare. 1 Megagram (Mg)=10^6 gram=1000 kg=1 tonnes=1.10 US metric tonnes.

DISCUSSION

The tree structural composition of the tropical forest of Southwestern Nigeria is predominantly hardwood species. For example, *Klaneidoxa gabonensis* (0.92 g/cm^3), *Nauclea diderichii* (0.67 g/cm^3), *Irvingia gabonensis* (0.77 g/cm^3), *Lophira alata* (0.89 g/cm^3), *Diospyros dendo* (0.90 g/cm^3) and *pentaclethra macrophylla* (0.84 g/cm^3) are part of the tree species that constituted the emergent layer. Some softwood species, however, are found in the emergent layer. *Triplochiton scleroylon* (0.3 g/cm^3), Bombax buonopozense (0.32 g/cm^3) and *Ceiba pentandra* (0.31 g/cm^3) where some of the softwood species. It was observed that the softwood species in the emergent layer have large stem diameters compared with the hardwood species even though the softwood species are numerically fewer at the emergent layer than the hardwood. This is contrary to the general belief that the growth rate of light-demanding trees is characterized by low density and average stems. The findings however supported other observations. [36] opined that the interspecific variations in wood density between tree species within a forest structure determine the relationships between stem diameter and that wood density decreases with stem diameters. The canopy layer had a mixture of hardwood species and softwood species with no definite order of magnitude. Also, some emergent tree species were found as canopy layer species in the drier extremes of the forests this may be because of temperature changes since anthropogenic activities may result in slight climatic variations within the forests [37]. According to [38], wood density can also serve as an indicator of timber quality and plant adaptation strategies to stress. It is as well expected that the wood density of emergent layers should be higher than the canopy layer. Besides, characterizing the emergent and canopy layers into a pioneer and shade-tolerant species may improve the understanding of intra and interspecific relationships and explain how local differences determine tree height, stem diameters, and biomass [38,39].

The Log 2 height–diameter allometry showed that the average tree height was 33.2 meters. According to [14] the Bayesian inference procedure improves predictions with higher accuracy when compared with measured tree heights. This result is consistent with field measurements in the study area which places the forest height range from emergent tree species to canopy layer tree species within the range of 48 meters to 12 meters [14,40-42]. The findings also agree with studies carried out in other forest reserves in southwestern and southeastern Nigeria [20].

Forest structure and carbon sink

Linkage exists between the tropical forest structure and the carbon stocks in southwestern Nigeria. The findings showed that carbon stock estimates correspond with the state of conservation as primary forests with intact forest structures produced higher carbon stocks than the degraded secondary forest. For example, Omo Forest Reserve (174 MgCa/ha^{-1}) also known as Queen Elizabeth Forest is the most conserved while Sasha Forest Reserve(78 MgCa/ha^{-1}) is the most degraded of the forests forming the complex. The result is similar to previous findings in the region [40-41], which generally surmised that deforestation and degradation affect gross productivity with an impact on the forest structure.

CONCLUSION

The Wood Density, Height-Diameter Allometry and error propagation using the AGBMonteCarlo in the Bayesian procedure offered a robust way for forest carbon accounting in Nigeria and other African countries with tropical forests without legacy inventory data. Besides, the flexibility of site-specific and species-specific wood density provided insight into the structural dynamics of the tropical forests and how anthropogenic activities and climatic alterations especially temperature may affect the ratio and distribution of emergent and canopy layer species within a forest structure. For these reasons, the tropical forest structure may be better identified with light-demanding and shade-tolerant tree species for the simplicity that light-demanding trees are found in the upper story while shade-tolerant species are found in the canopy layer and understory depending on age and forest degradation. Also, the species-specific wood density provided a more reliable biomass estimate than the generalized average wood density value for the tropics (0.5 g/cm^3).

In conclusion, the study has shown that the predominantly hardwood tree species which occupy the emergent layer can withstand stress from anthropogenic activities indicating forest resilience for future regeneration. Furthermore, the study shows a possibility of providing reliable regional carbon stock estimates in developing countries for Monitoring and Reporting Verification (MRV) projects when combined with a cutting-edge remote sensing approach for a wall to wall mapping over different vegetation types.

REFERENCES

1. Ali A, Mattsson E, Nissanka SP, Wang LQ. Topmost trees and foremost species underlie tropical forest structure, diversity and biomass through opposing mechanisms. For Ecol Manage. 2020;473:118-299.
2. Jayathunga S, Owari T, Tsuyuki S, Hirata Y. Potential of UAV photogrammetry for characterization of forest canopy structure in uneven-aged mixed conifer–broadleaf forests. Int J Remote Sens. 2020;41(1):53-73.
3. Lindenmayer DB, Margules CR, Botkin DB. Indicators of biodiversity for ecologically sustainable forest management. Conserv Biol. 2000;14(4):941-950.
4. Bohn FJ, Huth A. The importance of forest structure to biodiversity–productivity relationships. R Soc Open Sci. 2017;4(1):1605-1621.
5. Almeida DD, Broadbent EN, Zambrano AM, Wilkinson BE, Ferreira ME, Chazdon R, et al. Monitoring the structure of forest restoration plantations with a drone-lidar system. Int J Appl Earth Obs Geoinf. 2019;79:192-198.

6. Réjou-Méchain M, Tanguy A, Piponiot C, Chave J, Hérault B. biomass: an r package for estimating above-ground biomass and its uncertainty in tropical forests. Methods Ecol Evol. 2017;8(9):1163-1167.

7. Lewis SL, Sonké B, Sunderland T, Begne SK, Lopez-Gonzalez G, Van Der Heijden GM, et al. Above-ground biomass and structure of 260 African tropical forests. Philos Trans R Soc Lond, B, Biol Sci. 2013;368(1625):20120295.

8. Bouvet A, Mermoz S, Le Toan T, Villard L, Mathieu R, Naidoo L, et al. An above-ground biomass map of African savannahs and woodlands at 25 m resolution derived from ALOS PALSAR. Remote Sens Environ. 2018;206:156-73.

9. Kansanen K, Vauhkonen J, Lähivaara T, Seppänen A, Maltamo M, Mehtätalo L, et al. Estimating forest stand density and structure using Bayesian individual tree detection, stochastic geometry, and distribution matching. ISPRS J Photogramm Remote Sens. 2019;152:66-78.

10. Rodríguez-Veiga P, Quegan S, Carreiras J, Persson HJ, Fransson JE, Hoscilo A,et al. Forest biomass retrieval approaches from earth observation in different biomes. Int J Appl Earth Obs Geoinf. 2019;77:53-68.

11. Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WB, et al. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob Chang Biol. 2014;20(10):3177-90.

12. Piponiot C, Derroire G, Descroix L, Mazzei L, Rutishauser E, Sist P, et al. Assessing timber volume recovery after disturbance in tropical forests–A new modelling framework. Ecol Modell. 2018;384:353-69.

13. Teimouri M, Doser JW, Finley AO. ForestFit: An R package for modeling tree diameter distributions. arXiv preprint arXiv:1911.11002. 2019.

14. Zhang X, Duan A, Zhang J, Xiang C. Estimating tree height-diameter models with the Bayesian method. Sci. World J. 2014;2014.

15. Chave J, Muller-Landau HC, Baker TR, Easdale TA, Steege HT, Webb CO, et al. Regional and phylogenetic variation of wood density across 2456 neotropical tree species. Ecol Appl. 2006;16(6):2356-67.

16. Adekunle VA. Conservation of tree species diversity in tropical rainforest ecosystem of South-West Nigeria. J Trop For Sci. 2006:91-101.

17. Adepoju KA, Salami AT. Geospatial assessment of forest fragmentation and its implications for ecological processes in tropical forests. Landsc Ecol. 2017;10(2):19-34.

18. Okali DU, Ola-Adams BA. Tree population changes in treated rain forest at Omo Forest Reserve, south-western Nigeria. J Trop Ecol. 1987;3(4):291-313.

19. Onyekwelu JC, Mosandl R, Stimm B. Tree species diversity and soil status of primary and degraded tropical rainforest ecosystems in south-western Nigeria. J Trop For Sci. 2008:193-204.

20. Isichei AO. Omo biosphere reserve, current status, utilization of biological resources and sustainable management (Nigeria). UNESCO; 1995.

21. Lowe RG. Forestry and forest conservation in Nigeria. The Commonwealth Forestry Review. 1984:129-36.

22. Keenan RJ, Reams GA, Achard F, de Freitas JV, Grainger A, Lindquist E, et al. Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. For Ecol Manage. 2015;352:9-20.

23. Chave J, Andalo C, Brown S, Cairns MA, Chambers JQ, Eamus D, et al. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia. 2005;145(1):87-99.

24. Chave J, Riéra B, Dubois MA. Estimation of biomass in a neotropical forest of French Guiana: spatial and temporal variability. J Trop Ecol. 2001;17(1):79-96.

25. Chave J, Condit R, Aguilar S, Hernandez A, Lao S, Perez R, et al. Error propagation and scaling for tropical forest biomass estimates. Philos Trans R Soc Lond B Biol Sci. 2004;359(1443):409-20.

26. Yusuf HA, Oludipe JJ, Adeoye OO, Olorunfemi IE. Carbon Stocks in Aboveground and Belowground Biomass of Sub-Humid Tropical Forest in Southwestern Nigeria. Open Access Library Journal. 2019;6(8):1-2.

27. Ikemeh RA. *Boundary / Biodiversity survey of Omo – Oluwa -Sasha Forest Complex. Area 1: Omo Forest Reserve*. Retrieved from Lagos: 2009.

28. Oates JF, Dunn A, Greengrass E and Morgan BJ. Pan troglodytes sp. Ellioti. (Version 2.2). Retrieved 2012, from IUCN. 2003.

29. Gonzalez P, Asner GP, Battles JJ, Lefsky MA, Waring KM, Palace M, et al. Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. Remote Sens Environ. 2010;114(7):1561-75.

30. Chave J, Coomes D, Jansen S, Lewis SL, Swenson NG, Zanne AE, et al. Towards a worldwide wood economics spectrum. Ecology letters. 2009;12(4):351-66.

31. Flores O, Coomes DA. Estimating the wood density of species for carbon stock assessments. Methods Ecol Evol. 2011;2(2):214-20.

32. Zanne AE, Lopez-Gonzalez G, Coomes DA, Ilic J, Jansen S, Lewis SL, et al. Global Wood Density Database. 2009.

33. Boyle B, Hopkins N, Lu Z, Raygoza Garay JA, Mozzherin D, Rees T, et al. The taxonomic name resolution service: an online tool for automated standardization of plant names. BMC bioinformatics. 2013;14(1):1-5.

34. Feldpausch TR, Lloyd J, Lewis SL, Brienen RJ, Gloor M, Monteagudo Mendoza A, et al. Tree height integrated into pantropical forest biomass estimates. Biogeosciences. 2012;9(8):3381-403.

35. Molto Q, Hérault B, Boreux JJ, Daullet M, Rousteau A, Rossi V, et al. Predicting tree heights for biomass estimates in tropical forests. Biogeosciences. 2014;11(12):3121.

36. King DA, Davies SJ, Tan S, Noor NS. The role of wood density and stem support costs in the growth and mortality of tropical trees. J Ecol. 2006;94(3):670-80.

37. Djomo AN, Ngoukwa G, Zapfack L, Chimi CD. Variation of wood density in tropical rainforest trees. J For. 2017;4(2):16-26.

38. Chen L, Xiang W, Wu H, Lei P, Zhang S, Ouyang S, et al. Tree growth traits and social status affect the wood density of pioneer species in secondary subtropical forest. Ecol Evol. 2017;7(14):5366-77.

39. Phillips OL, Sullivan MJ, Baker TR, Monteagudo Mendoza A, Vargas PN, et al. Species matter: wood density influences tropical forest biomass at multiple scales. Surv Geophys. 2019;40(4):913-35.

40. AKINDELE SO. Tree species diversity and structure of a Nigerian strict nature reserve. Trop Ecol. 2013;54(3):275-89.

41. Oluwagbenga O, Orimoogunje I. Forest cover change and land use dynamics in Oluwa forest reserve, southwestern Nigeria. J Landsc Ecol. 2014;7:25-44.

42. Chave J, Coomes D, Jansen S, Lewis SL, Swenson NG, Zanne AE, et al. Towards a worldwide wood economics spectrum. Ecology letters. 2009;12(4):351-66.