Research Article

Modelling and Mapping of Aboveground Carbon of Oluwa Forest Reserve Using LandSat 8 TM and Forest Inventory Data

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This study was conducted in Oluwa Forest Reserve to assess and predict its aboveground carbon sequestration potentials using LandSat Thematic Mapper data. The Oluwa Forest Reserve, Ondo State, Nigeria, is recognized for its rich biodiversity and extensive size. To estimate its forest aboveground biomass and carbon should be complex and costly endeavour requiring the expertise of various professionals and equipment. Consequently, this study explored the use of Geographic Information System (GIS) and Remote Sensing (RS) technology using LandSat bands to estimate spectral indices in fitting linear models to predict the aboveground carbon sequestration potentials of the tropical rainforest ecosystem of Oluwa Forest Reserve. The observed aboveground carbon from sample plots and the estimated spectral indices were used to model the spread of aboveground carbon of Oluwa Forest Reserve. Positive linear relationship exists between the observed and the spectral indices data estimated. Therefore, linear models were fitted and the best-fit was determined using statistical measures. The aboveground carbon average estimated from the sample plots and the predicted were 150.70 t/ha and 149.80 t/ha, respectively. The coefficient of determination 94% and Root Mean Square Error = 6.38E-16, respectively were obtained statistically. The chosen model predicts the aboveground carbon spread of Oluwa Forest Reserve adequately. The study revealed that spectral data, GIS and RS are critical for large forest aboveground carbon modelling and mapping for efficiency.

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Introduction

Tropical rainforest ecosystems possess substantial stores of carbon, both aboveground and belowground (Yadav *et al*. 2022). Typically, these carbon reservoirs are held in the form of biomass found in various components such as tree trunks, roots, woody vegetation, organic matter in the soil, and litter on the forest floor. Among these components, the aboveground biomass of living trees contains the most extensive carbon stock (Adeniyi and Ajayi, 2017). It is also the component that is directly impacted by activities related to forest degradation and deforestation (Adewoye *et al*. 2015). This has sparked an interest in forest management for global climate mitigation, focusing on the estimation of carbon stock within forests (Akhlaq *et al*. 2015; Adeniyi and Ajayi, 2017). Within the tropical rainforest ecosystem, it is established that approximately 50% of tree biomass consists of carbon, primarily stored within the aboveground biomass of trees (Adewoye *et al*. 2015). As a result, the measurement of aboveground carbon stock play pivotal roles in obtaining precise estimates of forest carbon stocks for the United Nations′ Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) program, which focuses on measurement, reporting, and verification of forest carbon.

Various methods have been employed to estimate the aboveground biomass of tropical rainforests, including field-based inventory (both direct and indirect approaches), remote sensing, and the use of allometric equations. Among these methods, the direct field inventory is widely regarded as the most accurate for estimating aboveground biomass and carbon stock. However, it′s worth noting that this method is time-consuming, labour-intensive, and expensive (Onyekwelu, 2004; Adewoye *et al*. 2015; Adeniyi and Ajayi, 2017). Nonetheless, remote sensing, which is an indirect method, is typically applied to extensive land areas and provides the potential for assessing forest carbon stocks through satellite data, as demonstrated by Baccini *et al*. in (2008). But, the accuracy and reliability of the results depend on the availability of ground-based inventory data (Adewoye *et al*. 2015).

Estimations and mapping of aboveground carbon using remote sensing data commonly involve the correlation of ground-based inventory data with spectral reflectance, including vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI), *etc* (Sarker and Nichol, 2011). Despite this, challenges related to data saturation can arise when utilizing remote sensing imagery for aboveground carbon modelling in tropical rainforests, particularly in areas with substantial biomass but can be amended (Foody *et al*. 2003; Adewoye *et al*. 2015; Adeniyi and Ajayi, 2017).

The primary objective of this study is to evaluate the carbon stocks present in the Oluwa Forest Reserve and employ remote sensing data to model and create a comprehensive map illustrating the forest reserve's carbon sequestration potential. The goal is to precisely depict the distribution of carbon based on the most strongly correlated spectral index reflectance values. By amalgamating precise field inventory data with remote sensing information, we developed a highly accurate and dependable model for assessing carbon sequestration potential of Oluwa Forest Reserve. This method is crucial for reporting of forest carbon to the Clean Development Mechanism (CDM) under the Kyoto Protocol of the United Nations Framework Convention on Climate Change, as it enhance understanding of carbon balance within the forest ecosystems (Akhlaq *et al*. 2015; Adeniyi and Ajayi, 2017).

Study Area

This study was carried out in Oluwa Forest Reserve, Ondo State, Nigeria. This forest reserve is situated in Odigbo Local Government Area of Ondo State, Nigeria and lies between Latitude 6° 38′ 24″ - 6° 57′ 36″ N and Longitude 4° 28′ 48″ - 4° 52′ 48″ E and covers an area of 829 km^2. Annual rainfall in Oluwa Forest Reserve ranged between 1700 and 2200 mm with mean annual temperature of 26°C (Ogunjemite and Olaniyi, 2012). The relative humidity is high and uniform, ranged between 75% and 95%. Oluwa Forest Reserve soils are predominantly ferruginous tropical, typical of the variety found in intensively weathered areas of the rainforest ecosystem of South-western, Nigeria. The soils are well-drained, mature, red, stony and gravely in upper parts of the sequence (Ogunjemite and Olaniyi, 2012). Again, Onyekwelu *et al*. (2008) reported that Oluwa Forest Reserve has a texture of topsoil with mainly sandy loam. The vegetation of the reserve belongs to tropical rainforest with species such as *Melicia excelsa*, *Terminalia superba* and *Triplochiton scleroxylon*, *etc*.

Ground-based Biomass and Carbon Assessment

The materials used for this study include girth tape, meter tape, compass, ranging poles, flagging tape, Global Positioning System (GPS), relaskop and recording sheet. The girth tape was used to measure the Diameter at Breast Height (Dbh) and diameter at the base of trees. The metre tape, compass, flagging tape and ranging pole were used to lay temporary plots. Relaskop was used to measure upper diameters, and the tree height.

Plot layout and selection

Square grids of 30 m x 30 m was created in ArcGIS and overlaid on the shapefile of study area. Grids that fell out from the boundary of the shapefile were removed and the remaining grids were numbered. Twenty (20) grids were randomly selected from the forest reserve shapefile and laid as temporary sample plots for data collection purpose using the southwest corner coordinates value as starting point.

Data Collection

All the tree species within the sample plot with Dbh ≥10 cm were measured. Stems with forked or branched at Dbh point or below were considered as two individual trees as report by Ibrahim *et al*. (2018). In the plots, the trees were identified by forest taxonomist and their scientific names recorded. Measurements was restricted to the following tree variables; Dbh, diameter at the base (Db), diameter at the middle (Dm), diameter at the top (Dt) and tree height.

Wood Density

Tree species densities were obtained from literatures (African wood density and International Council for Research in Agroforestry databases). The forest reserve mean density was adopted for trees that the density was not found from the density database.

Methods and Data Analysis

Volume Estimation

The Newton's formula was used to estimate the tree species volumes for this study (Equation 1).

$$\text{Volume} = \frac{\pi h}{24}\left(D_b^2 + 4D_m^2 + D_t^2\right) \qquad \text{(Equation 1)}$$

Where:

Volume = Volume of tree (m^3), $\pi = 3.142$, h = Tree height (m), D_b = Diameter at the base (m), D_m = Diameter at the middle (m), D_t = Diameter at the top (m).

Estimation of biomass

Biomass of each tree was estimated using the volume and density as obtained for respective tree species and Equation 2 was employed.

$$\text{Biomass} = \text{Density} \times \text{Volume} \qquad \text{(Equation 2)}$$

Estimation of Carbon

Tree biomass obtained in Equation 2 was used to estimate carbon stock for each tree. The standard multiple factor of 0.5 was used for conversion of biomass to carbon stock (Equation 3) as adopted by Losi *et al*. (2003).

$$\text{Carbon} = 0.5 \times \text{Biomas} \qquad \text{(Equation 3)}$$

GIS and Remote Sensing Biomass/Carbon Mapping

The plot biomass/carbon values obtained from the ground-based assessment were correlated with the spectral indices values calculated from the respective points of the corresponding plots as used for this study.

Spectral indices Extractions

Four (4) spectral indices (Table 1) were selected for this study because they indicate one biophysical characteristic or the other and conditions of vegetation as reflected as true nature depict. These four spectral indices are; Normalised Difference Vegetation Index (NDVI), Greenness Normalised Difference Vegetation Index (GNDVI), Soil Adjusted Vegetation Index (SAVI) and Enhanced Vegetation Index (EVI). These spectral indices represent quantification of vegetation as well as vegetation greenness (Adeniyi and Ajayi, 2017). In addition, these various spectral indices have statistical correlation with biomass/carbon data (Deo 2008).

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Index	Equation	Constant	Author
Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{\mathrm{b5} - \mathrm{b4}}{\mathrm{b5} + \mathrm{b4}}$		Rouse. *et. al.,* 1974
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(1 + \mathrm{L})\mathrm{b5} - \mathrm{b4}}{\mathrm{b5} + \mathrm{b4} + \mathrm{L}}$	L=0.5	Huete (1988)
Greenness Normalised Difference Vegetation Index (GNDVI)	$GNDVI = \frac{\mathrm{b5} - \mathrm{b3}}{\mathrm{b5} + \mathrm{b3}}$		Gitelson. *et. al.,* 1996
Enhanced Vegetation Index (EVI)	$EVI = \frac{\mathrm{G}(\mathrm{b5} - \mathrm{b4})}{(\mathrm{b5} + \mathrm{C1b3} - \mathrm{C2b2}) + \mathrm{L}}$	G=2.5 L=1 C1=6 C2=7.5	Huete (1997)

Table 1. LandSat-derived spectral indices and their equations

Regression and Evaluation

The models employed in this study were constructed in a linear fashion, and this formation depended on the data distribution observed in the scatter plots. To assess the performance of the model(s), various statistical measures of goodness of fit were utilized, including Root Mean Square Error (RMSE), coefficient of determination (R^2), and residuals, among others.

The most strongly correlated spectral indices were selected as independent variables to predict the aboveground carbon content within the study area. Furthermore, the chosen model was applied to create a spatial distribution of aboveground carbon within the study area.

Results

The values of aboveground biomass and carbon vary across the plots. Plot 2 had the highest aboveground carbon with 195.31 t/ha, followed by plot 9 with 185.54 t/ha. The lowest plot aboveground carbon was recorded for plot 20 with 118.98 t/ha (Table 2).

Plot Number	Observed Aboveground Carbon (t/ha)	Predicted Aboveground Carbon (t/ha)
1	143.47	153.41
2	195.31	165.32
3	127.09	134.75
4	136.55	144.35
5	135.41	153.48
6	138.78	141.39
7	122.85	112.43
8	146.31	138.41
9	185.54	178.44
10	121.77	122.34
11	171.45	183.45
12	160.31	149.21
13	185.43	147.38
14	170.16	190.01
15	125.94	115.64
16	174.37	169.74
17	158.22	161.81
18	155.81	167.21
19	140.33	138.98
20	118.98	128.18
Mean	**150.704**	**149.797**

Table 2. Plots aboveground carbon (AGC)

Modelling Using Geographic Information System and Remote Sensing

There were moderate correlations observed between the recorded aboveground carbon (AGC) data and some of the spectral indices, ranging from 0.29 to 0.60 within the Oluwa Forest Reserve. However, a majority of the calculated spectral indices exhibited strong correlations with the observed AGC, surpassing the 0.5 threshold, indicating robust linear relationships among them. Worthy of note, the Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI), and Green Normalized Difference Vegetation Index (GNDVI) showed the highest correlations with the observed AGC values for the Oluwa Forest Reserve. Consequently, these spectral indices were selected as candidates for explanatory variables (as shown in Table 3).

However, only EVI exhibited a high level of significance in model construction, particularly when applied to transformed AGC data. Among the various models developed, a logarithmically transformed model with a single explanatory variable (EVI) was judged the most suitable for the study. This decision was based on the model's simplicity, significance, and its alignment with other predefined criteria.

To verify the predictive capacity and accuracy of the chosen model, a comparison was made between the generated data and the observed data, as well as an analysis of the residual plot distributions. Among the models evaluated, model number 4, emerged as the best spectral model, achieving a coefficient of determination (R^2) value of 0.94. This indicates that the selected model can predict the aboveground carbon content of the Oluwa Forest Reserve with a high level of accuracy, estimated at 94%.

No.	MODEL	R^2	AdjR^2	RMSE	SIG.
1	AGC = 12.06 + 21.64 (EVI) - 102.94 (GNDVI) + 5.44 (NDWI)	0.93	0.92	1.25E-15	*
2	LnAGC = 2.98 + 5.46 (EVI) - 24.96 (GNDVI) + 2.29 (NDWI)	0.93	0.92	9.16E-16	*
3	AGC = 6.76 + 13.81 (EVI)	0.93	0.92	5.55E-16	***
4	LnAGC = 2.24 + 4.38 (EVI)	0.94	0.94	6.38E-16	***

Table 3. AGC Spectral Indices Models

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Spatial Distribution of AGC

The aboveground carbon (AGC) values, derived from the spectral indices model within the study area, were utilized to create a spatial distribution map of aboveground carbon in the study area. The chosen spectral indices model yielded AGC estimates for the forest reserve that exhibited minor differences when compared to the observed values, and these differences were not statistically significant ($P < 0.05$).

Specifically, the selected spectral indices model estimated the average aboveground carbon to be approximately 149.80 metric tons per hectare, while the observed AGC was 150.70 metric tons per hectare. Using these AGC values from the model, an AGC map of the Oluwa Forest Reserve was generated. The colours on the map corresponded to the AGC content as predicted by the model, with green indicating higher carbon content and decreases as carbon content decreased (Fig. 1).

This study harnessed Landsat 8 Thematic Mapper data to develop a straightforward linear model, and employed to map the spatial distribution of aboveground carbon within the forest reserve. The logarithmically transformed data with a single explanatory variable (the spectral index) was identified as the most suitable for this study.

Additionally, an allometric equation, incorporated with spectral indices data as explanatory variables, was re-presented as Equation 4 for this study. Consequently, this allometric equation is recommended for accurately predicting aboveground carbon in the Oluwa Forest Reserve and other forest reserves sharing similar characteristics.

$$\mathrm{LnAGC} = 2.24 + 4.38(EVI) \qquad \text{(Equation 4)}$$

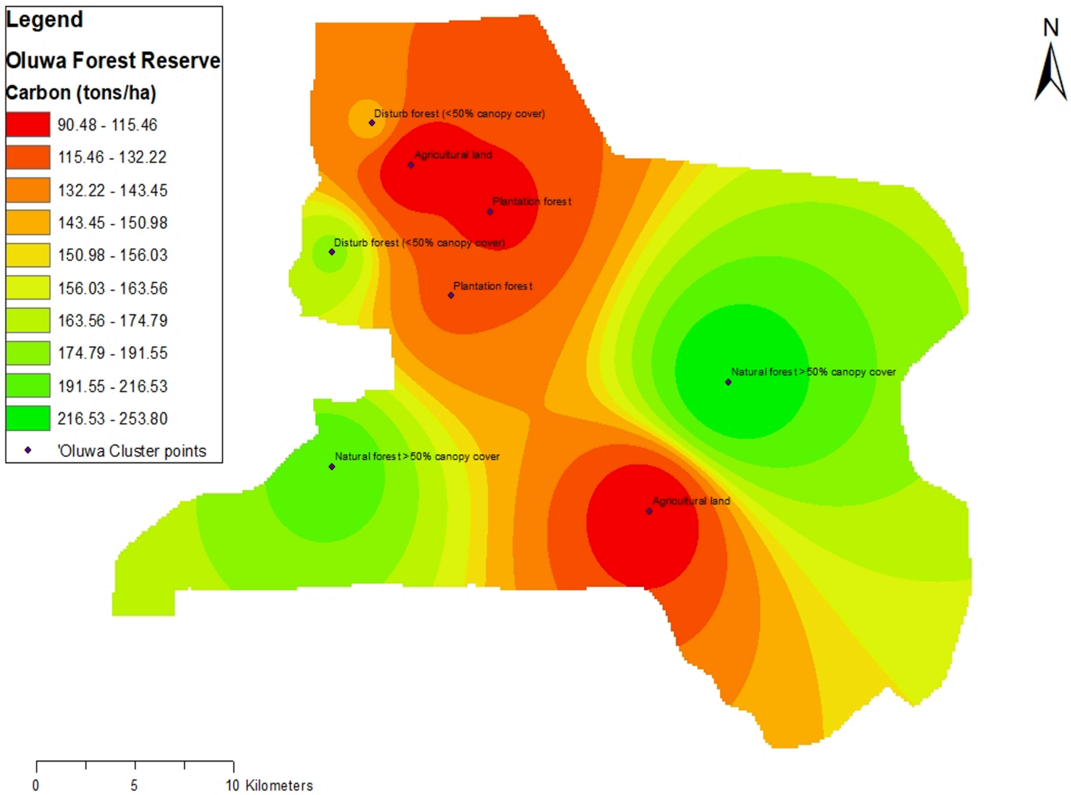

Fig. 1: Spatial distribution of aboveground Carbon of Oluwa Forest Reserve

Discussions

The density of green leaves, which represents the carbon accumulation of trees in optical sensors, is determined by the ratio and quantity of chlorophyll within the leaves, as well as the reflection of near-infrared (NIR) radiation and the absorption of red radiation (Ji *et al*. 2009; Adeniyi and Ajayi, 2017). The spectral indices model with the highest coefficient of determination (R^2) value, measuring 0.94, was adjudged to be the most suitable for the study area. This finding aligns with the results of Adewoye *et al*. (2015), who reported a coefficient of determination (R^2) of 0.936 in their study titled "Estimating Aboveground Biomass of the Afromontane Forests of Mambilla Plateau Using Quickbird and in Situ Forest Inventory Data". The model featuring EVI as the explanatory variable demonstrated the most effective predictive capacity, producing results that closely aligned with the observed data, with no significant differences noted. This outcome is in line with the conclusions drawn by Gizachew *et al*. (2016) in their paper titled "Mapping and Estimating the Total Living Biomass and Carbon in Low-

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Biomass Woodlands using Landsat 8 CDR Data." In their study, they also found that spectral indices models were proficient in predicting biomass and carbon. The correlation of EVI to aboveground carbon was 60% for this study. The result of the study is higher than what was reported by Gizachew *et al*. (2016) who reported correlation coefficient of 0.50. The observed variation could stem from variances in the tree species found within the forest estate, as the level of reflectance is primarily influenced by leaf structure and the quantity of intercellular space within the leaves (Itkonen, 2012; Gizachew *et al*. 2016; Dupiau *et al*. 2022). Logarithmic transformation was applied to models using EVI as the independent variable to predict AGC and the outcome of this investigation align with the findings of certain authors who identified logarithmic transformation as the optimal approach when constructing biomass and carbon models (Onyekwelu, 2004; Adeniyi and Ajayi, 2017).

Spatial Distribution of Carbon with Spectral Indices Model

The aboveground carbon value obtained for this study is higher than the findings of Adeniyi and Ajayi, (2017) who reported mean aboveground carbon of 81.20 t/ha in Omo Biosphere Reserve. In addition, the result of this study is higher than the findings of authors (*e.g.* Baccini *et al*. 2008; Gizachew *et al*. 2016). These study reported 80±7 t/ha and 138 t/ha, respectively. Furthermore, the result of this study is higher than what Vroh *et al*. (2015) who reported 173.59 ± 50.85 t/ha for Yapo protected forest and 122.55 ± 15.84 t/ha as the above-ground biomass accumulation of Natural Voluntary Reserve (NVR) forest. However, the carbon findings in this study exhibited a favorable comparison with the report of Adewoye *et al*. (2015), who reported an aboveground biomass of 300.10 t/ha, considering that this study applied a 50% conversion of biomass to carbon. The differences and similarities in the findings of these studies could be attributed to the methodologies utilized as reported by Oke *et al*. (2020) and biophysical characteristics of the forest landscape (Petrokofsky *et al*. 2012; Akhlaq *et al*. 2015). The aboveground carbon distribution within Oluwa Forest Reserve was produced by employing AGC values derived from plot data and spectral indices modelling. The resulting map illustrates the variance in carbon accumulation within the study area. Consequently, this research has showed areas with higher carbon accumulation, providing valuable insights for forest managers regarding regions with greater carbon sequestration potential within the forest reserve landscape.

Conclusion and Recommendation

This study was conducted to model and map the aboveground carbon content within Oluwa Forest Reserve, utilizing a combination of forest inventory data and Landsat imagery data through remote sensing techniques. Within this research, the application of Landsat 8 data was explored to establish a straightforward linear model, serving as the foundation for estimating carbon stocks, and map the spatial distribution.

This study specifically used logarithmic model developed and adjudged the best to create distribution map of aboveground carbon in the study area. Consequently, this approach suggests that the allometric equation developed in conjunction with the spectral index can be effectively utilized to estimate the aboveground carbon content of Oluwa Forest Reserve with a satisfactory level of accuracy with 94% confidence level. Hence, the study recommend the adoption of this equation for the study area and other forest reserves sharing similar characteristics.

Competing interests

We (authors) declare that there is no competing interests.

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Declarations

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