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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 research was carried out within the Oluwa Forest Reserve to evaluate and forecast its capacity for aboveground carbon sequestration using data from the Landsat Thematic Mapper. The Oluwa Forest Reserve, situated in Ondo State, Nigeria, is renowned for its abundant biodiversity and vast expanse. Assessing the forest's aboveground biomass and carbon traditionally involves intricate and expensive processes necessitating the expertise of diverse professionals and specialized equipment. Hence, this study investigated the utilization of Geographic Information System (GIS) and Remote Sensing (RS) technology, employing Landsat bands to calculate spectral indices and construct linear models for predicting the aboveground carbon sequestration potential of the tropical rainforest ecosystem within the Oluwa Forest Reserve. The measured aboveground carbon from sample plots, alongside the estimated spectral indices, was utilized to simulate the distribution of aboveground carbon across the Oluwa Forest Reserve. A positive linear correlation was identified between the observed data and the estimated spectral indices. Consequently, linear models were developed, and the most suitable model was determined through statistical analysis. The average aboveground carbon estimated from the sample plots was 150.70 tons per hectare (t/ha), closely aligning with the predicted value of 149.80 t/ha. Statistical analysis yielded a coefficient of determination of 94% and a Root Mean Square Error of 6.38E-16. These results indicate that the selected model accurately predicts the distribution of aboveground carbon within the Oluwa Forest Reserve. This study underscores the importance of spectral data, GIS, and RS in the efficient modelling and mapping of aboveground carbon in extensive forest ecosystems.

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Introduction

Tropical rainforest ecosystems harbour significant reserves of carbon, both above and below the ground[1]. Typically, these carbon stores exist in various forms within different components such as tree trunks, roots, woody vegetation, organic material in the soil, and litter on the forest floor. Among these components, the aboveground biomass of living trees holds the largest carbon stock[2], making it particularly susceptible to activities associated with forest degradation and deforestation[3]. This has prompted increased interest in forest management strategies for global climate mitigation, with a focus on estimating carbon stocks within forests[4][2].

Within tropical rainforest ecosystems, it is well established that approximately 50% of tree biomass consists of carbon, and it is primarily stored within the aboveground biomass[3]. Consequently, accurate measurement of aboveground carbon stocks plays a crucial role in obtaining precise estimates of forest carbon stocks for initiatives such as the United Nations' Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) program, which emphasizes the measurement, reporting, and verification of forest carbon.

Although various approaches have been utilized to estimate the aboveground biomass of tropical rainforests, including field-based inventory methods (both direct and indirect), remote sensing techniques, and the utilization of allometric equations, among these methodologies, direct field inventory is widely recognized as the most precise for estimating aboveground biomass and carbon stock. However, it is important to acknowledge that this method is characterized by being time-consuming, labour-intensive, and costly[5][3][2].

Nevertheless, remote sensing, an indirect method, is commonly applied to vast land areas and offers the potential for evaluating forest carbon stocks using satellite data, as demonstrated by Baccini *et al*.[6]. The accuracy and reliability of these results are contingent upon the availability of ground-based inventory data[3].

The process of estimating and mapping aboveground carbon using remote sensing data often involves correlating ground-based inventory information with spectral reflectance, which may include various vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), among others[7]. However, challenges related to data saturation can emerge when employing remote sensing imagery for aboveground carbon modelling in tropical rainforests, particularly in regions with substantial biomass. Nevertheless, these challenges can be addressed[8][3][2].

In recent years, there has been a significant global push to enhance the efficiency of optical data for the precise estimation of forest aboveground biomass and carbon, focusing on leveraging object features. Extensive literature reviews demonstrate a consistent enhancement in aboveground biomass and carbon estimations with object features. Texture extracted from moderate-resolution Landsat data has proven effective in modelling aboveground biomass and carbon across numerous forests[9][2]. Likewise, textural features derived from high-resolution data sources such as Worldview-2, IKONOS, and QuickBird have been successfully employed in modelling and estimating forest aboveground biomass and carbon[3]. The utilization of derived object features in biomass modelling exhibits variability across geographical regions and the types of optical data employed. However, there is a prevailing consensus that object features extracted from images may offer greater suitability for biomass and carbon modelling, particularly in the diverse and complex landscapes of tropical rainforests.

The Oluwa Forest Reserve is renowned for its abundant biodiversity and vast expanse of land with tree species that have high carbon stock values[10]. The

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main aim of this study is to assess the carbon stocks within the Oluwa Forest Reserve and utilize remote sensing data to construct a comprehensive map illustrating the reserve's potential for carbon sequestration. Our objective is to accurately depict the distribution of carbon based on spectral index reflectance values with the strongest correlation. By integrating precise field inventory data with remote sensing information, we have developed a highly precise and reliable model for evaluating the carbon sequestration potential of the Oluwa Forest Reserve. This methodology is essential for reporting forest carbon to the Clean Development Mechanism (CDM) under the Kyoto Protocol of the United Nations Framework Convention on Climate Change, as it enhances our understanding of the carbon balance within forest ecosystems[4][2].

Study Area

This research was conducted within the Oluwa Forest Reserve, located in the Odigbo Local Government Area of Ondo State, Nigeria. The reserve spans an area between Latitude 6° 38′ 24″ - 6° 57′ 36″ N and Longitude 4° 28′ 48″ - 4° 52′ 48″ E, covering approximately 829 square kilometres. The annual rainfall in the reserve varies from 1700 to 2200 mm, with an average annual temperature of 26°C[11]. The relative humidity remains consistently high, ranging from 75% to 95%. The soils in the Oluwa Forest Reserve are predominantly ferruginous tropical, typical of extensively weathered regions within the rainforest ecosystem of South-western Nigeria. These soils are well-drained, mature, and characterized by a reddish colour, stones, and gravel in their upper layers[11]. Additionally, Onyekwelu *et al*.[12] noted that the topsoil texture in the reserve is primarily sandy loam. The vegetation in the reserve is classified as tropical rainforest and includes species such as *Melicia excelsa*, *Terminalia superba*, and *Triplochiton scleroxylon*, among others.

Ground-based Biomass and Carbon Assessment

The equipment utilized in this study comprised a girth tape, meter tape, compass, ranging poles, flagging tape, Global Positioning System (GPS), relaskop, and recording sheets. The girth tape facilitated the measurement of Diameter at Breast Height (Dbh) and the diameter at the base of trees. The meter tape, compass, flagging tape, and ranging poles were employed in setting up temporary plots. The relaskop was employed to measure upper diameters and tree height.

Plot Layout and Selection

Square grids of 30 m x 30 m were created in geographic information system software (ArcGIS) and overlaid on the shapefile of the study area. Grids that fell outside 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 out as temporary sample plots for data collection purposes using the southwest corner coordinates value as the starting point.

Data Collection

All the tree species within the sample plot with Dbh ≥10 cm were measured. Stems that forked or branched at the Dbh point or below were considered as two individual trees, as reported by Ibrahim *et al*.[13]. In the plots, the trees were

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identified by a forest taxonomist, and their scientific names were recorded. Measurements were 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 literature (African wood density and International Council for Research in Agroforestry databases). The forest reserve mean density was adopted for trees whose density was not found in the density database.

Methods and Data Analysis

Volume Estimation

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), π = 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 the 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 the carbon stock for each tree. The standard multiple factor of 0.5 was used for the conversion of biomass to carbon stock (Equation 3) as adopted by Losi *et al*.[14].

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

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 another and conditions of vegetation as reflected as true nature depicts. 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[2]. In addition, these various spectral indices have a statistical correlation with biomass/carbon data[15].

Index	Equation	Constant	Author
Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{b5 - b4}{b5 + b4}$		Rouse. *et. al.,* 1974
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(1 + L)b5 - b4}{b5 + b4 + L}$	L=0.5	Huete (1988)
Greenness Normalised Difference Vegetation Index (GNDVI)	$GNDVI = \frac{b5 - b3}{b5 + b3}$		Gitelson. *et. al.,* 1996
Enhanced Vegetation Index (EVI)	$EVI = \frac{G(b5 - b4)}{(b5 + C1b3 - C2b2) + L}$	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 validated with an independent data set before being applied to create a spatial distribution of aboveground carbon in the study area.

Results

The values of aboveground biomass and carbon vary across the plots. The average aboveground carbon estimated from the sample plots was 150.70 tons per hectare (t/ha), closely aligning with the predicted value of 149.80 t/ha (Table 2).

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Variable	Observed Carbon	Predicted Carbon
Mean	150.70	149.80
Standard Error	7.32	3.66
Median	85.94	42.97
Mode	149.30	148.09
Standard Deviation	131.78	65.89
Sample Variance	17366.18	4341.54
Kurtosis	16.16	16.16
Skewness	3.28	3.28
Range	1044.46	522.23
Minimum	12.66	6.33
Maximum	1057.12	528.56
Sum	41349.54	20674.77
Count	324.00	324.00

Table 2. 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

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 decreasing as carbon content decreased (Fig. 1).

This study harnessed Landsat 8 Thematic Mapper data to develop a straightforward linear model and employed it 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.

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

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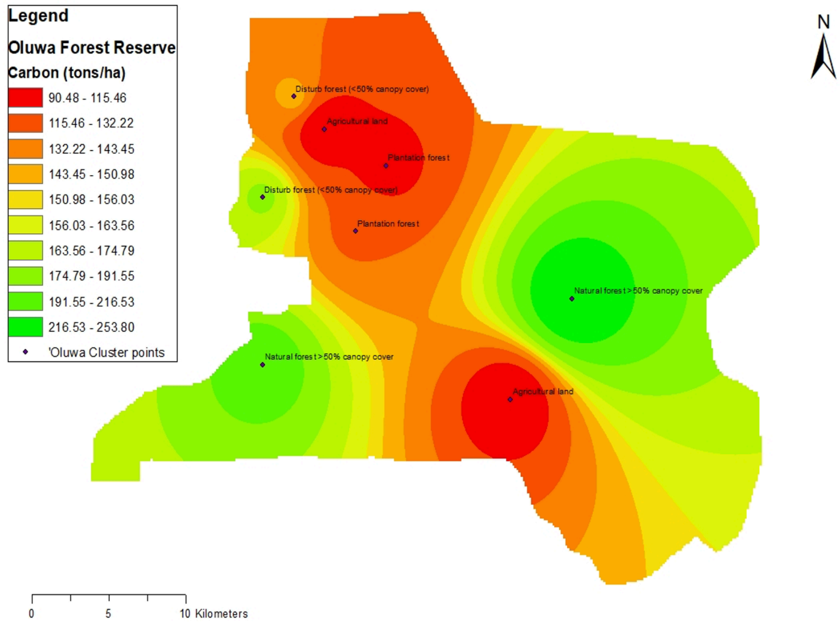

Figure 1. Spatial distribution of aboveground Carbon of Oluwa Forest Reserve

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[16][2]. 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.[3], 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.[17] in their paper titled "Mapping and Estimating the Total Living Biomass and Carbon in Low-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.[17] who reported a 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[17][18]. Logarithmic transformation was applied to models using EVI as the independent variable to predict AGC, and the outcome of this investigation aligns with the findings of certain authors who identified logarithmic transformation as the optimal approach when constructing biomass and carbon models[5][2].

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,[2] who reported a 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.* [6][17]). This study reported 80±7 t/ha and 138 t/ha, respectively. Furthermore, the result of this study is higher than what Vroh *et al*.[19] 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 favourable comparison with the report of Adewoye *et al*.[3] 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*.[20] and the biophysical characteristics of the forest landscape[21][4]. 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 shown areas with higher carbon accumulation, providing valuable insights for forest managers regarding regions with greater carbon sequestration potential within the forest reserve landscape.

Conclusions and Recommendations

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 mapping the spatial distribution. This study revealed the potential capacity of the forest reserve to sequester carbon. It is, therefore, imperative to manage this endowment properly to ensure the continuous provision of these forest services.

This study specifically used a logarithmic model developed and adjudged the best to create a distribution map of aboveground carbon in the study area. Consequently, this study recommends that the allometric equation developed in conjunction with the spectral index be used to estimate the aboveground carbon content of Oluwa Forest Reserve with a satisfactory level of accuracy and a 94% confidence level.

Permissions Statement

Necessary permissions for conducting fieldwork and data collection within the Oluwa Forest Reserve were obtained from the relevant authorities in Ondo State, Nigeria (Ondo State Ministry of Natural Resources, Department of Forest Resources Management).",
"Data Availability Statement": "The datasets generated during the current study, including field inventory data and derived spectral indices, are available from the corresponding author on reasonable request.

Author Contributions

Conceptualization, methodology, data collection, and original draft preparation: E.A.; Data collection, analysis, and original draft preparation: A.A.; Writing—review and editing: B.L.B. All authors have read and agreed to the published version of the manuscript.

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Declarations

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