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Modelling and Comparison of Above-Ground Tree Biomass of Omo Biosphere Reserve Using Field and Landsat 8 Data

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Authors' contributions

This work was carried out in collaboration between both authors. Author PAA designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Author AE managed the analyses of the study, managed the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

Forest ecosystems occupied substantial vacuum in the balance of atmospheric carbon and thereby control global carbon cycle as well as climate change effect. Assessment of forest biomass value determines the role of forest as carbon offset entity. The selection of appropriate biomass assessment method and/or the use of reliable allometry are prime factors to carbon calculation of a forest. This study developed and compared biomass models as well as produced acceptable allometry equation for the study area and forest similar characteristics. It was revealed that forest biomass could be assessed with the use spatial image with spectral bands, and indices calculated. Different spectral indices correlated with one another as well as correlated with biomass observed data. Though, correlation level differs across the various indices considered but Enhance Vegetation Index (EVI) gave the best fit based on the criteria set for this study ($Ln\,AGTB = 7.981 + 10.799\,(EVI)$). Two forms of biomass equation including the observed Above-ground Tree Biomass

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(AGTB) value were compared and the result shows that there were no significant differences amongst the different estimation methods. Carbon spatial distribution pattern was generated with the chosen spectral index model.

Keywords: EVI; biomass; carbon; climate; indices; spatial; AGTB; spectral.

1. BACKGROUND OF THE STUDY

The estimation of forest biomass is an essential aspect of studies of carbon storage and carbon balance of forests [1]. Since forests play an important role in global carbon budget as carbon sinks and emission when disturbed or altered [2,3]. Plant growth and development reflects the possibility of removing CO_2 from the atmosphere through photosynthesis especially the plant growth rate, or increment, which influences the performance of forest ecosystems to uptake carbon. Also, emissions are caused by forest or biomass losses (i.e. harvest, disturbance and mortality). The resultant effect of these two activities affects the results of carbon emissions and removals which are also expressed as total carbon stock changes of an area.

The assessment of carbon storage in the forest biomass has gained special interest as a result of the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol. As a result of these agreements, countries who signed this treaty are mandated to estimate and report CO_2 emissions and removals by forests through effective Measuring Reporting and Verified (MRV) systems that comply with the guidelines of the Intergovernmental Panel on Climate Change. This process is considered as an integral part of Reduce Emissions from Deforestation and forest Degradation (REDD+) actualization within their member country [4]. REDD+ programme of the United Nations deploys results-based finance for incentive on carbon emissions reduction, based on a functional forest carbon measurement, reporting and verification (MRV) system [5]. Nevertheless, technical challenges in measurement, reporting and verification have substantially contributed to the lack of progress for implementation of REDD+ programme of the agreed countries. A functional measurement, reporting and verification to support REDD+ programme requires estimates of the area of forest loss and gain as well as the corresponding carbon stock and changes [5]. These data are needed for the estimation of the actual emissions and the construction of forest reference emissions level, as a benchmark against which the actual emissions are compared [5]. A combination of accurate field inventory and remote sensing are expected to provide the carbon emission and sink results.

The estimation of forest biomass over a large area and accurate reporting without expertise either from sample tree or stand could be very difficult and almost impossible. Though, it was the destructive method which encompasses cutting of trees, excavating their components, drying and weighing of the components to obtain biomass. These processes could be very tedious and therefore, attentions should focus more in the use and development of techniques to estimate forest biomass from easily measurable tree characteristics (e.g stem diameter, height etc.). These techniques, is generally known as allometry which usually involve relationships between tree biomass and parameters such as stem diameter and/or height [6,7,8].

This study aimed at developing and established a Landsat 8 based equation for the assessment of aboveground tree biomass in the study area. The specific objectives includes; (i) develop and compare biomass equation obtain from different assessment method methods, (ii) produce spatial distribution of carbon over the study area with the selected spectral index model.

2. METHODS

2.1 Study Area

This study was conducted in a polygon of 10,200.57 hectares as Omo Biosphere Reserve, which was carved out for this study based on vegetation cover with no traces of encroachment. The study area lies approximately between latitudes6^o 55'' 12.0' to 7^o 10'' 12.0'N and longitudes4^o 13'' 12.0' to 4^o 24'' 0.0'E within the high forest zone in south-western of Nigeria (Fig. 1). Originally, the biosphere reserve covers about 14,660 hectares of land including its core area and buffer zone, which was constituted a Strict Nature Reserve in 1949 and Biosphere Reserve in 1977 respectively [9].

The climate of the study area is humid tropical. The biosphere reserve exhibit two seasons: rainy and dry seasons as obtained in the southwest geopolitical zone of Nigeria. The wet (rainy) season starts from March and ends in November while dry season lasts from December to February. Annual rainfall ranges from 1700 to 2200 mm while annual temperature and average daily relative humidity are 26℃ and 80%, respectively. Rainfall distribution is bi-modal with a marked decline in August and at the peaks in July and September. Average elevation is about 123 m in Omo Biosphere Reserve [9]. Geologically, the reserve rest on crystalline rocks of the undifferentiated basement complex which in the southern parts is overlain by Eocene deposits of sand, clay and gravel as reported by [10]. Thus, the soils are predominantly ferruginous tropical, typical of the variety found in intensively weathered areas of basement complex formations in the rainforest zone of south-western Nigeria [11]. The soils are well drained, mature, red, stony and gravely in upper parts of the sequence [9].

2.2 Sampling Design

The map of Omo Biosphere Reserve (i.e. undisturbed natural forest) was carved and gridded into plots of 30 m by 30 m as obtained in the Landsat image pixel obtained for this study. Ten [10] sample plots of 0.09 ha was randomly selected from the map and located on the field with the use of Global Positioning System (GPS) during the data collection stage of the study.

2.3 Data Collection and Measurements

All standing trees (with minimum Dbh of 10 cm) within each sample plot were identified by a forest taxonomist and their Dbh was measured in the field using a girth tape. Afterwards the trees in each sample plot were grouped into species groups and two mean trees per species were selected for AGTB assessments. The total heights, diameters at the base, middle and top of all the mean trees were measured using Spiegel Relaskop, which were used for the volume estimations. Newton's formula (Equation 1) [12] was used to estimate the standing volume of each mean tree.

$$V_{total} = \frac{\pi h}{24}\{D_b^2 + 4D_m^2 + D_t^2\} \qquad (1)$$

Where:

V_{total} = Volume of the stem
h = Total Tree Height
∏ = 3.142
D_b = Diameter at the base
D_m = Diameter at the middle
D_t = Diameter at the top.

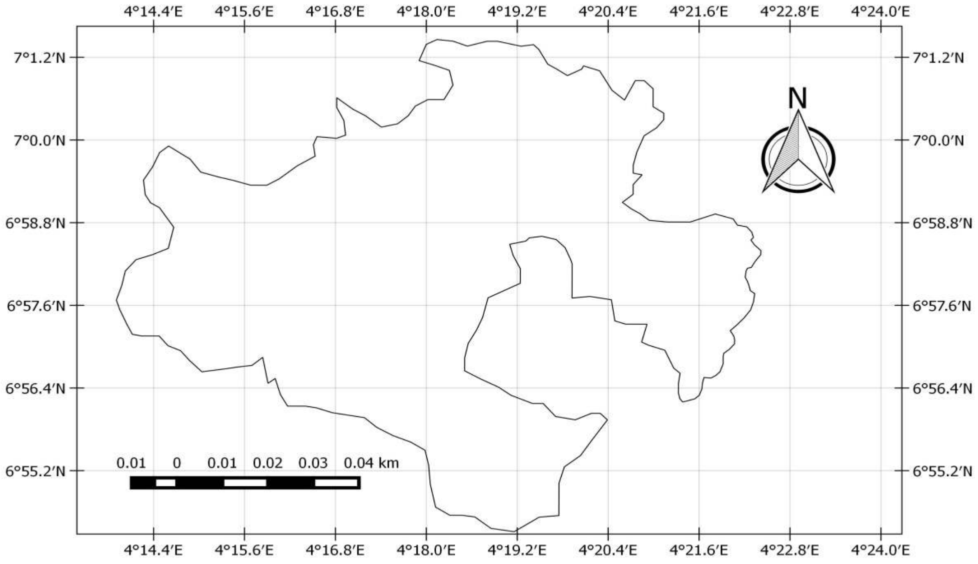

Fig. 1. Map showing the study area

2.4 Estimation of Stem Core Volume

A core sample of each of the two mean trees of each species group was extracted with an increment borer at the breast height point (i.e. 1.3 m). Shape of the stem core sample is cylindrical and therefore the equation (2) was employed to estimate the volume of each core sample.

$$V_s = \frac{\pi d_s^2}{4} l \quad (2)$$

Where:

d_s = diameter of the core sample, (cm)l = length of the core sample, (cm)
∏ = 3.142
v_s = volume of the core sample, (m)

2.5 Conversion of Stem Volume and Core Volume to above Ground Tree Biomass

A non-destructive sampling method was used in this study to estimate the above-ground tree biomass. The two mean trees per species group selected were used for AGTB estimation. A core sample of each of the two mean trees of each species was extracted with an increment borer at the breast height point (i.e. 1.3 m). The length of the core extracted using the increment borer was measured in centimetres. Core diameter was also measured for the sample and their average was taken since only one increment borer with one extraction tube was used for the entire study. The core samples were oven-dried at 75ºC to a constant weight and the mass measured. Dry weight of the core sample was measured in grams using an electronic weighing balance. Tree AGTB was calculated for each stem by using the equation (3) below [13].

$$AGTB = \frac{W_d \times Vol}{V_s} \quad (3)$$

Where:

Vol = total stem volume (m^3)
W_d = oven dry weight of the core sample (kg)
$AGTB$ = Above-ground Tree Biomass (kg)

2.6 Carbon Stock Assessment

The above-ground tree biomass estimated was used to determine the amount of carbon stock in each of trees, plots and forest stand since it is known that carbon is 50% of biomass estimates [14] as obtained in equation [4].

$$Carbon = Biomass\ X\ 0.5 \quad (4)$$

Where:

0.5 = Constant
Biomass = Above-ground Tree Biomass (kg)

Carbon per plot was obtained by adding the carbon of all the mean trees within the plot. Carbon per hectare was computed by first summing the carbon of all the sample plots selected for this study and finding their mean, and secondly by multiplying the mean carbon per plot by the number plots per hectare (i.e. 11.111 plots). Also per hectare values was multiplied by number of hectare within the biosphere reserve to obtain carbon for the entire stand.

2.7 Modelling of Biomass/Carbon

Land sat TM image covering the whole study area was obtained during the same season as that of the research and it was cloud free. Projection of the image was defined to WGS_1984 [15]. In the search for best predictive and acceptable biomass model; seven (7) spectral bands (2 - 9) were extracted from Land sat 8 image of the study area to calculate seven (7) spectral indices (NDVI, SAVI, EVI, GNDVI, NDMI, NBR AND NBR2) considered for this present study (see Table 1). These spectral indices were chosen for this study because they indicate biophysical characteristics and conditions of vegetation as well as represent vegetation quantity and greenness [16,17]. Although these spectral indices are moderately or highly correlated with one another, but each of these indices comes with some advantages [17]. The above-ground tree biomass data obtained from each sample plot were expressed in tonnes and correlated with the spectral indices calculated.

Also, in attempt to provide the best predictive model(s); tree parameter, mean Dbh from each sample plot was used as a predictor of AGTB as reported by some authors [e.g.7,18].

2.8 Data Analysis

Regression analysis between the spectral indices and the AGTB data were performed in order to quantify the relationship between dependent variable (AGTB) and one or more independent variables (spectral indices). Both the relationship between AGTB and spectral indices; AGTB and tree variable (Dbh) were examined to provide the best predictive model(s).

Table 1. Landsat-derived spectral indices used to estimate AGB

Index	Equation	Constant	Author
Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{\mathrm{b5} - \mathrm{b4}}{\mathrm{b5} + \mathrm{b4}}$		Rouse *et al.,* (1974) [19]
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) [20]
Greenness Normalised Difference Vegetation Index (GNDVI)	$GNDVI = \frac{\mathrm{b5} - \mathrm{b3}}{\mathrm{b5} + \mathrm{b3}}$		Gitelson*et al.,* (1996) [21]
Enhanced Vegetation Index (EVI)	$EVI = \frac{(\mathrm{b5} - \mathrm{b4})}{(\mathrm{b5} + 6\,(\mathrm{b4}) - 7.5\,(\mathrm{b2}) + 1)}$	L=1 C1=6 C2=7.5	Huete (1997) [22]
Normalized Burn Ratio (NBR)	$NBR = \frac{\mathrm{b5} - \mathrm{b7}}{\mathrm{b5} + \mathrm{b7}}$		Miller and Thode, (2007) [23]
Normalized Difference Moisture Index (NDMI)	$NDMI = \frac{\mathrm{b5} - \mathrm{b6}}{\mathrm{b5} + \mathrm{b6}}$		[24]
Normalized Burn Ratio-2 (NBR2)	$NBR2 = \frac{\mathrm{b6} - \mathrm{b7}}{\mathrm{b6} + \mathrm{b7}}$		[23]

The best fitting model(s) were determined based on the goodness of fit statistics; highest R^2, lowest RMSE and highest AdjR^2. After determined the best model (s) for the predictions of AGTB with spectral indices as well as tree variable, the spatial distribution pattern of carbon of the study area was mapped using the data obtained from the respective model.

2.9 Comparison between AGTB Estimation Models

The resultant AGTB values from both models alongside the field AGTB(i.e. the observed AGTB value and the predictive AGTB values from both spectral indices and tree variables models) were compared with Analysis of Variance (ANOVA) to test for significant difference between the AGTB values ($P \leq 0.05$). The ten plots AGTB obtained from the field as well as those obtained from AGTB predictive models (i.e. both the spectral indices and tree variable values) were used in the comparison test.

3. RESULTS

3.1 Modelling of Above-ground Tree Biomass (AGTB)

There were high correlation coefficient between the observed AGTB data and some of the indices (ranges from 0.45 – 0.98) which justified the candidate predictor(s) amongst the spectral indices. Although, majority of the calculated spectral signature values correlated with observed AGTB values, and also there exist either moderate or high correlation between the various spectral signatures. But Enhances Vegetation Index (EVI) produced the highest correlation to the observed AGTB values and this justified the use of this signature as explanatory variable.

Logarithmic transformed model with one explanatory variable was obtained based on the simplicity of model and their significance as well as estimated accuracy with little or no error. The predictive capability and accuracy of selected model(s) for this study was confirmed with the data generated which indicated little or no difference from the field AGTB (see Table 4).

This model with EVI as explanatory variable was chosen as the best spectral model to predict AGTB with (0.945 and 0.118 as Adj$R^2$and RMSE respectively) (Table 2). Also, Diameter at Breast Height (Dbh) was chosen as preferred tree variable to predict AGTB with (0.788 and 0.231as Adj$R^2$and RMSE respectively) (Table 3).

The EVI index equation (Table 2) and Equation number 1 (Table 3) as selected models were reproduced as Equation 7 and 8 respectively. These model has been tested with prove of adequate and significant as explanatory variables (see Table 4). The AGTB values from the three methods (i.e. observed AGTB; spectral index model and tree variable predicted AGTB) considered for this study were generated with the equations/models obtained as well as observed AGTB values from the field (see Table 4).The Equation 7 was used to estimate predicted AGTB with spectral signature (EVI) as explanatory variable while Dbh was used as explanatory variable to obtain predicted AGTB in Equation 8.

$$Ln\ AGTB = 7.981 + 10.799\ (EVI) \quad (7)$$

$$Ln\ AGTB = -1.230 + 0.170\ (Dbh) \quad (8)$$

3.2 Comparison between Biomass Estimation Methods

The comparison test carried out revealed that there are no significant differences among the treatments (i.e. observed AGTB and the two predictive AGTB values) used for this study (see Table 5). Though, spectral signature predicted AGTB was slightly higher followed by observed AGTB value and the tree variable predicted AGTB gave the lowest but there are no significant difference among these values ($P<0.05$). The result of the test shows that the *P-value* (0.98979) is greater than 0.05 which means that there is no significant difference amongst the AGTB estimation methods considered for this study. More also, F-calculated is less than F-critical value which also signified that there are no significant difference amongst the three AGTB estimation methods (see Table 5).

Table 2. Equations/Models generated with spectral indices

Index	Equation	R^2	AdjR^2	RMSE
EVI	LnAGTB = 7.981 + 10.799(EVI)	0.951	0.945	0.118
NDMI	LnAGTB = -3.366 + 30.922(NDMI)	0.911	0.900	0.159
GNDVI	LnAGTB = 6.918 + 0.000(GNDVI)	0.870	0.842	0.214
NBR	LnAGTB = -7.089 + 28.835(NBR)	0.825	0.803	0.223
SAVI	LnAGTB = -7.505 + 24.941(SAVI)	0.779	0.751	0.250
NBR2	LnAGTB = -5.484 +51.963 (NBR2)	0.774	0.746	0.253
NDVI	LnAGTB = -6.252 +32.677(NDVI)	0.753	0.723	0.264

AGTB = dependent variable; EVI = (independent variable); Ln = natural logarithm

Table 3. Equations/models generated with tree variable

Equation No.	Equation	R^2	AdjR^2	RMSE
1	LnAGTB = -1.230 + 0.170(Dbh)	0.811	0.723	0.231
2	LnAGTB = 3.420 + 0.844(Dbh)	0.811	0.723	0.231
3	LnAGTB = 0.292 + 0.170(Dbh)	0.811	0.723	0.231
4	LnAGTB = 0.292 + 1.185(Dbh)	0.811	0.723	0.231
5	LnAGTB = 6.170 - 79.351(Dbh)	0.826	0.804	0.222
6	LnAGTB = 3.696 + 0.000(Dbh)	0.820	0.797	0.226

AGTB = dependent variable; Dbh = (independent variable); Ln = natural logarithm

Table 4. Resultant above-ground tree biomass from three methods

Plot No.	Stem (ha^{-1})	Mean Dbh	Observed AGTB (t/ha)	Predicted AGTB (t/ha)	
				Tree variable (Dbh)	Spectral indices (EVI)
1	311	17.9	156.52	281.24	108.10
2	233	19.3	46.44	164.97	58.17
3	467	19.4	253.02	181.61	159.69
4	556	22.1	147.61	88.03	152.74
5	489	23.1	276.16	139.28	278.69
6	311	23.1	144.56	205.48	146.73
7	389	23.7	100.25	67.64	99.05
8	356	24.3	147.68	202.13	233.73
9	367	24.4	197.50	165.43	248.31
10	456	26.2	132.15	86.36	138.81
Sum			**1601.88**	**1582.16**	**1624.01**
Mean			**160.19**	**158.22**	**162.40**
Study area total			**1634007.78**	**1613897.35**	**1656587.73**

Table 5. Showing analysis of variance (ANOVA) for biomass estimation methods

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	0.76446	2	0.38223	0.01026	0.98979	3.35413
Within groups	1005.67	27	37.2471			
Total	1006.44	29				

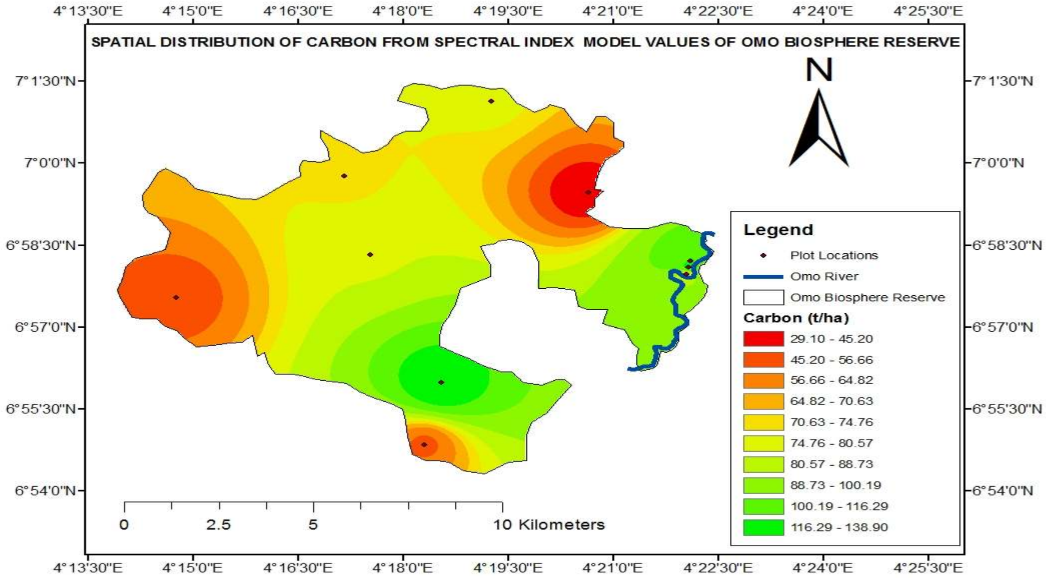

Fig. 2. Showing spatial distribution of carbon spread of Omo biosphere reserve with spectral indices model data

3.3 Spatial Distribution Pattern of Carbon with Spectral Indices Model

The AGTB values derived from spectral index model (EVI) was used to map the spatial distribution of carbon of the study area. The accumulation and spread of carbon within the reserve tailored towards the water source where vegetation is denser with high diameter trees (see Fig. 2). The spectral index (EVI) model estimated the biomass/carbon of the reserve little higher than the tree variable (Dbh) model as well as observed AGTB but there are no significant difference amongst them. The spectral index (EVI) model had 162.40 t/ha and a total of 1,656,587.73 tons of AGTB for the 10,200.57 hectares covered for this study, and the model with diameter (Dbh) as explanatory variable had 1435.06 Mg/ha and a total of 1,613,897.35 tons of AGTB for the study area while the observed AGTB (i.e. AGTB measured from the field) had 160.19 t/ha and 1,634,007.78 tons of AGTB for the area covered for this study (see Table 4). Though, slight variations exist amongst the three methods estimation of AGTB /carbon of the study area but there are no significant difference at ($P<0.05$).

4. DISCUSSION

4.1 Modelling of Biomass/Carbon

The proportion and amount of chlorophyll in the leaf and the reflectance of near infrared (NIR) radiation as well as absorption of red radiation determined the proportion to green leaf density which represents the biomass accumulation of trees in optical sensor [17]. The spectral index (EVI) produced the highest correlation (0.98) and the rest of the spectral indices had high correlation except the NBR and NBR2 which produced 0.45 correlations. The EVI offered the highest correlation amongst the spectral signatures, and this is consistent with the findings of [5]. But the correlation of EVI to aboveground biomass of 0.98 produced in this study is higher than 0.50 as obtained by [5]. The logarithmic transformed models were chosen to predict above ground biomass which is also consistent with finding of some authors which generated models for biomass prediction [e.g. 25,7].

4.2 Comparison between Biomass Estimation Methods

The comparison of three methods of biomass estimation considered for this study shows that there are no significant difference among them. Though, slight variations exist but it does not differ significantly. This finding is consistent with authors who generated biomass equations and compared them with observed biomass values [e.g. 7,26,27]. Therefore, these models are recommended for use in predicting the aboveground tree biomass accumulation in Omo Biosphere Reserve.

4.3 Spatial Distribution Pattern of Carbon with Spectral Indices Model

Omo Biosphere Reserve had mean biomass accumulation of 162.40 t/ha as well as mean carbon sequestration of 81.20 t/ha (Table 2) since carbon is 50% of biomass. The above-ground tree biomass value obtained for this present study is double the value of biomass reported by [5] and also higher than the biomass value reported by [28]. Both of whom reported 80 ±7 t/ha and 138 t/ha respectively. But the value obtained is lower to what [29] reported for a protected forest in Côte d'Ivoire; who reported 347.17 ± 101.70 t/ha and 245.09 ± 31.68 t/ha as the above-ground biomass accumulation of Yapo protected forest and Natural Voluntary Reserve (NVR) forest, respectively.

The spatial distribution pattern of the carbon was mapped using the 50% of the above-ground biomass data. The Biosphere reserve has accumulated a total of 1,656,587.73 tonnes of biomass and 828,293.90 tonnes of carbon (Table 2). This value of biomass/carbon obtained for this study exceeds the report of [5] which gave 140 ± 7 Mt for area of 15, 700 km^2. These values of biomass/carbon content show the importance of the area in carbon sequestration and climate change mitigation potential.

5. CONCLUSION AND RCOMMENDATION

This study was prepared to model and map with the selected model as well as compared the two allometric equations with observed forest biomass data in the quest to provide the best allometry for the study area and forest with similar characteristics.

Logarithmic equation was selected with single explanatory variable for both the spectral index and tree variable models, and compared their output with observed forest biomass value which shows that there are no significant difference at ($P<0.05$) level of significance. This study facilitated the use of Landsat 8 data for the development of a simple linear model which provides the basis for mapping forest carbon, estimating carbon stock and detecting its spatial distribution. It thereby means that allometry equations developed with spectral index can be used to estimate the above-ground tree biomass of the study area with acceptable accuracy.

These equations generated for this study are recommended for use in predicting the aboveground tree biomass accumulation in Omo Biosphere Reserve.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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