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Article

Modeling of Above Ground Biomass for Selected Indigenous *Acacia Species* in Omo-Gibe Woodland Ecosystem, South Western Ethiopia

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Abstract: Allometric equations are used to estimate accurate biomass and carbon stock of forests. However, in Ethiopia only few allometric equations as compared to its floral diversity and species-specific allometric equations for *Acacia* species are still not developed in Ethiopia. The numbers of tree marked for sampling are Fifty-four (54) using preferential sampling. Diameter at breast height, wood density and tree height were collected as independent variables to predict species specific dry biomass of *Acacia* species. The new species-specific allometric models have been performed using linear regression analysis in the R software. The Above ground biomass (AGB) have been validated using quantitative statically using the pantropic model. Six candidate models have been developed for each species and four best models for each species of dry biomass was selected based on goodness-of-fit statistics and equation performance analysis of the candidate models.

The best model for predicting above ground biomass for *Acacia seyal is* $0.20636*((DBH^2)H\varrho)^{0.53167}$, for *Acacia polyacantha* is $7.26982((DBH)^2H\varrho)^{0.21750}$, for *Acacia ethibcia* is $29.01898*((DBH)^2H\varrho)^{0.21518}$ and for *Acacia toritolis* is $3.82427*((DBH)^2H\varrho)^{0.16748}$. The selected models are the best performing (P> 0.01) and higher adjusted R^2 (>80%) and has lower Akaike's Information Criteria **(**AIC) and residual standard error (RSE) values as comparing the rest of the model. The validation of new developed biomass model using Tukey test indicated that significant variation of mean biomass (P<0.05) between the new developed model and the generalized model. The statistics model performance analysis of Nash-Sutcliffe efficiency (NSE) value is approaching to one, indicating that the new developed model has better performance model as compared with generalized model. Moreover, the percent bias of the new developed models is close to zero which indicates that the site-specific biomass models have more accurate estimator and the generalized biomass models have overestimated biomass for the four *Acacia* species.

Keywords: acacia species; allometric equation; above ground biomass; carbon stock

1. Introduction

Estimating biomass is a significant task in evaluating the amount of carbon stock in tropical forests [1]. The accurate measurement of biomass is crucial for the assessment of carbon stock toward understanding carbon variations in response to world climate changes [2, 3], as well as ecological processes such as wood production and nutrient cycling [4]. Even though there is no commonly accepted allometric model for estimation of above ground, biomass allometric equation is an important approach for sustainable management of forest and mitigation of climate change [5].

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Equations developed elsewhere may not accurately predict local biomass due to differences in tree architecture (e.g. number of stems, height to branching), age, diameter, stand density, cultivars, site conditions (climate and soils), and management practices [6]. Management practices influence biomass production and allocation within trees in the landscape [7]. For example, variation in pruning and coppicing may affect the rate of biomass accumulation [8] and pruning can change biomass without changing DBH [9, 10]. Therefore, modeling allomtric at local level is important for elaborating biomass explicitly.

Most of the previous equations were developed using destructive method. However, using such destructive method is tedious and time consuming [11] and it is costly to implement in the whole strata of a forest area [12]. On the other hand, non-destructive method for developing allometric equation is less time and energy consuming as well as economically viable. Such methods are readily applicable in degraded woodlands containing threatened species. Moreover, destructive measurements have high probability of being limited by technical, financial and legal considerations [13]. In Ethiopia cutting indigenous trees is forbidden by law making and the application of destructive method less applicable [14-16]. This makes it necessary to replace destructive sampling method by an alternative method such as semi destructives.

Few allometric equations exist for sub-Saharan Africa including Ethiopia, as a result, using of generalized allometric equations developed from other continents have been established for carbon accounting and applied as default for African settings [13]. Although such extrapolation may create uncertainty during carbon accounting. Moreover, there is no a specific model for Acacia species in south west forest of Ethiopia and elsewhere in the entire country. Species specific allometric equation for indigenous trees and available information is largely lacking in Ethiopia [17]. South western Ethiopia has abundant remnant Acacia woodland ecosystems providing productive and protective ecosystem services [18].

Therefore, this research is set out to develop species-specific allometric models for estimating above ground biomass of *Acacia seyal*, *Acacia polyacantha*, *Acacia toritolis*, and *Acacia ethibcia* that are the most dominant species in the Acacia woodland ecosystems of the south-western Ethiopia. In addition, the study aims at analysis and validation of model performance using goodness-of-fit statistics and quantitative statistics through comparing the generalized equation. In so doing the study contributes provide scientific input for informed policy decision making on forest management and carbon trading.

2. Materials and Methods

2.1. Description of the study area

Ghibe Valley is a section of the Om-Gibe basin which is geographically located in the southwestern part of the country, 180 km to the South West of Addis Ababa (Figure 1). The area lies within the geographical coordinates of 037^{0}15'-037'40'E longitude and 08^{0}00'-08^{0}30'N latitude (Figure 1) with mean elevation of 1050 m. The vegetative physiognomy of the area is dominated by wooded grassland (61% cover) [19] and low land plants which found mainly *Acacia* species [20]. Moreover, *Ficus sycomorus*, *Tapura fischeri*, *Melanodiscus oblongus*, *Celtis integrifolia* and *Trichilia roka* were also found dominantly in upstream forest sites [21].

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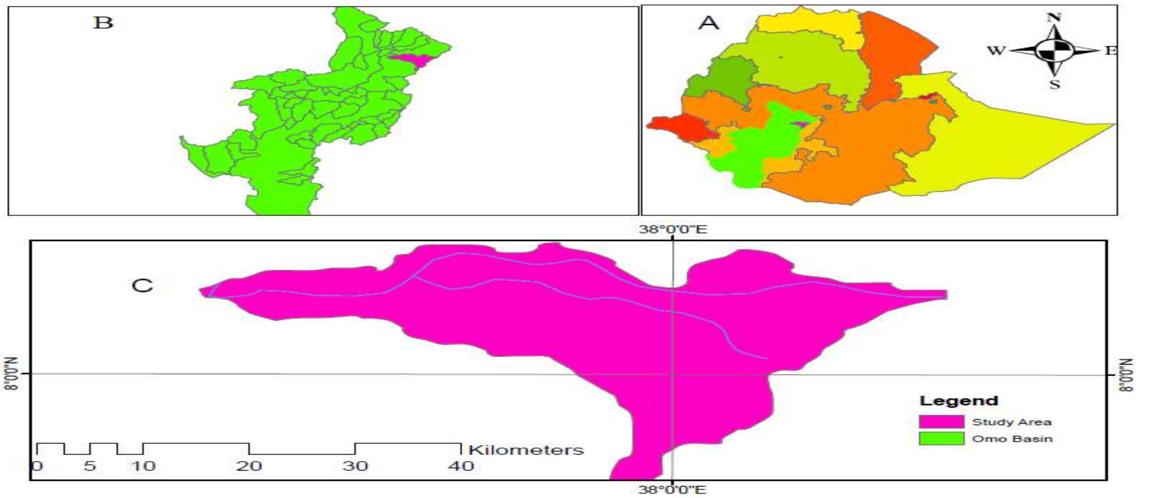

Figure 1: A) Shows location of Omo-Gibe Basin in Ethiopia; B) Shows location of study area in the Omo-Gibe Catchment and C) Shows the study area watershed

2.2. Design and sampling techniques

The most dominant species are used for developing the species specific allometric equations [22]. The dominant species are *Acacia polyacantha, Acacia seyal, Acacia toritolis* and *A. ethibcia*. Bekele-Tesemma and Tengnäs [23] species description is used to identify the species. The location of the sample plots within the woodland were taken using preferential systematic sampling and sample selection of trees were chosen based on as representativeness, diameter distributions and diameter breast height (DBH). A total of fifty-four (54) individual trees were selected representing the four *Acacia* species and tagged for sampling of biomass data collection.

For easy development of the model, the trees were divided into separate architectural elements as trimmed small branch, untrimmed small branch, untrimmed large branch and trunk. Due to the difference in moisture content, tree material was separated into leaves, twigs, small branches, large branches and stem [10]. Two calculations were required to estimate the dry biomass of the untrimmed (still standing) part of the trees (one for the small branches and the other for the large branches and the trunk [16, 24]). Diameter breast Hight was measured with a measuring tape at 1.30 m above ground from the uphill side of the tree [25]. On the other hand, total tree height was measured by climbing up to the top of the trees. The length, diameter at each end of the climbing stem (fragmented stem section) and large branches with a small end diameter (SED) greater or equal to 10 cm over bark were measured [26].

Volume over bark of stump, stem and large branches (branches whose diameter ≥ 10 cm) was calculated from the cross-sectional measurements using Smalian formula, $Vi = Li (D^{2}1i + D^{2}2i)$ [27] since each of the measured stem section is taken as a perfect cylindrical assumption. Where **Vi** is the volume of the section **i, Li** its length, and **D1i** and D2i are the diameters of the two extremities of section i.

The total volume of each sample tree was obtained by summing the volume of the sectional measurements. Then, the total volume was multiplied by the average wood density to estimate the biomass of the stump, bole, and large branches. The dry biomass of the large branches and trunk is

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the product of mean wood density and total volume of the large branches and trunk [16] (Formula 1).

$$B_{dry\ section} = mean\ \ \rho\ \times \Sigma iVi, \tag{1}$$

and Mean wood density (ρ) is calculated by

$$\rho = \frac{B_{aliquot\ dry\ wood}}{V_{aliquot\ fresh\ wood}}, \tag{2}$$

If ρ is expressed in g/cm^{-3}, volume Vi expressed in cm^3, both length **L**i and diameters **D**1i and **D**2i expressed in cm.

The dry biomasses of the untrimmed small branches were then calculated using a model between dry biomass of total trimmed of the tree and basal diameter. Linear type equations are often used:

$$B_{dry\ branch} = a + bD, \tag{3}$$

Where a, b are model parameters (intercept and slope) and D branch basal diameter. As a result, the total dry biomass of untrimmed branches per a tree is:

$$B_{untrimmed\ dry\ branch} = \sum J(a + bDJ), \tag{4}$$

Where the sum was all the untrimmed small branches and DJ is the basal diameter of the sh ort branch.

2.2.1. Trimmed Leaves and small branch

The tree branches were trimmed using local machete and the twigs and attached foliage (i.e., the leaves) were carefully removed from each trimmed branch and mixed in bulk [26] and weighed as fresh weight (total and sample weights) in the field [28]. A total number of 200 fresh biomass samples, and subsample of 250–600 gram for trimmed wood, and 50-150 gram for 200 samples of leaves biomass were collected. The leave component was brought to Wolkite University at department of natural resource management experiment laboratory for dry biomass determination, dried to constant mass for 72 h at 105 °C [10]. The fresh volume of the wood aliquot was measured in the laboratory in order to determine mean wood density (ρ). The dry biomass of leaves from the trimmed branches ($B_{trimmed\ dry\ leaf}$) and the fresh biomass of the wood from the trimmed branches ($B_{trimmed\ dry\ wood}$) were determined by using Equation 5 and 6.

$$\text{Btrimmed dry leaf biomass} = \frac{B_{aliquot\ dry\ leaf}}{B_{aliquot\ fresh\ leaf}} \times \text{Btrimmed fresh leaf}, \tag{5}$$

$$\text{Btrimmed dry leaf biomass} = \frac{B_{aliquot\ dry\ wood}}{B_{aliquot\ fresh\ wood}} \times \text{Btrimmed fresh wood}, \tag{6}$$

In order to determine gross tree biomass for short branch, the trimmed biomass multiplied by the number short branches. Similarly, the gross biomass of the leaves of a tree was computed from the product of trimmed leave biomass and total number of short branches per tree.

2.4. Allometric model development

Allometric power function equations, $\mathbf{y = ax^b}$ and their linear equivalents, ln(y) = a + b× ln(x) were used to determine biomass of the study species. where **y** is the dependent variable, x is the independent variable, and a is intercept coefficient, b the scaling exponent, were used to predict

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biomass. The following allometric relationships were tested according to Kuyah, Dietz [29] for the study.

$$\ln(y) = a+b\times\ln(dbh), \quad (7)$$

$$\ln(y)=a+b\times\ln(dbh)+c\times\ln(H), \quad (8)$$

$$Ln(y)= a+b\times\ln(\rho), \quad (9)$$

$$\ln(y)=a+b\times\ln(dbh)+c\times\ln(\rho), \quad (10)$$

$$\ln(y)=a+b\times\ln(dbh)+c\times\ln(H)+d\times\ln(\rho), \quad (11)$$

$$\ln(y)=a+\ln(dbh)^2\rho H, \quad (12)$$

Where dbh is the diameter at breast height, H is the height and ϱ is the wood density. The equations were fitted by including ln(dbh), ln(H) and ln(ρ) as separate predictors, so that they each can be attributed their own scaling parameter.

2.5. Statistical analysis

The data obtained were analyzed using R statistical software (version 3.2.2). Before establishing the allometric equation, scatter plots were used to see whether the relationship between independent and dependent variable was linear or outlier using the R statistical software packages [30]. All of the variables were log-transformed in order to apply linear models and developed single-variable and multiple-variable allometric equations for each species to select best equation for the species. Besides, constructed a set of multispecies AGB regression equations by including all individuals dendrometric variables for the four species (n = 54). Here, single-variable refers to either diameter (D), height (H), and density (ϱ) while multiple-variable refers to the combination of two or three of these factors. The independent variables were DBH, H, wood density (ϱ) and $(DBH)^2H\varrho$ whereas the dependent variable was the dry weight of total AGB. Equation performance was carried out using various goodness-of-fit statistics, namely, the coefficient of determination (R^2), Bayesian Information Criterion (BIC) [31, 32] and standard error of estimate (SEE). The best species-specific and multispecies statistical model equation was selected according to the highest R^2 and the lowest Akaike Information Criterion(AIC) and lowest Residual standard error (RSE) values [33]. The models were ranked according to each goodness-of-fit statistic, the ranks summed and sums ranked to give an overall model performance rank [34].

3. Results

The minimum DBH is 29 cm for *Acacia toritolis* and the maximum is 170 cm for *Acacia polyacantha* whereas height varied from 5.5 m to 22 m (**Table 1**). Acacia seyal, Acacia ethibcia and *Acacia toritolis* have lower DBH whereas *Acacia polyacantha* has higher DBH. There has been also correlation between height and DBH (r^2 =0.32) for each tree's species. Similarly, dimeter breast height of larger branch is positively corelated with the smaller branch for each species.

Table 1. Mean dendrometric characteristic of sample of the four *Acacia* tree species

Tree species	Value	DBH	DBHb	H
	Mean	88.17	29.50	8.25
A.seyal	Max	170.00	13.00	12.00

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	Min	33.00	49.00	5.50
	N	12.00	12.00	12.00
	Mean	93.17	31.20	13.33
	Max	155.00	66.00	22.00
	Min	34.00	7.00	7.00
A.polyacantha	N	18.00	18.00	18.00
	Mean	88.92	29.16	13.08
	Max	134.00	44.00	20.00
	Min	39.00	7.00	8.00
A. ethibcia	N	12.00	12.00	12.00
	Mean	85.08	30.50	13.83
	Max	143.00	47.00	20.00
	Min	29.00	10.00	8.00
A. toritolis	N	12.00	12.00	12.00

Note: DBH=diameter breast height, DBHb=diameter basal height, H=height of the trees

3.2 Trimmed biomass weight

The average wood aliquot moisture content of *Acacia sayal*, *Acacia polycantha*, *Acacia ethibcia Acacia toritolis* was 0.56, 0.41, 0.50 and 0.59 grams, respectively. Similarly, the average leaf aliquot moisture content of these species was 0.46, 0.38, 0.44 and 0.44 g rams, respectively (Table 2). The result showed that, the moisture content trimmed leaves were higher than the moisture content of trimmed branch wood of the trees. The trimmed small branch dry biomass for *Acacia sayal*, *Acacia polycantha*, *Acacia ethibcia* and *Acacia toritolis* is 266.17, 155.00, 222.25, 251.08 gram, respectively. It is important determinant factor for predicting untrimmed small branch for each *Acacia* tree species (**Table 2**).

Table 2. Mean dry weight of trimmed branch biomass by species

Species Name	Men fresh Wt (g)	Mean oven dry Wt (g)	Mean X wood (g)	Mean L Wt fresh (g)	Mean L Wt after oven (g)	averag e X L (g)	Mean wood density	Btrim med dry(g)
A.sayal	400	228.33	0.56	82.17	37.83	0.43	0.45	266.17
A.polyacantha	300.56	122.39	0.41	82.44	32.61	0.38	0.36	155.00
A. ethibcia	350.00	175.42	0.50	105.33	46.83	0.44	0.39	222.25
A.toritolis	329.17	200.33	0.59	112.58	50.75	0.44	0.37	251.08

3.1. Wood density

There was significant variation in mean values of wood density trees in four species sampled in this study vary among sample trees and species (Figure 2). The mean wood density of *Acacia toritolis, Acacia polyacantha, Acacia ethibcia and Acacia seyal* was 0.37, 0.36, 0.39, and 0.45, in g/cm^3, respectively. The maximum wood density is less than 0.7 g/cm^3 and the minimum is 0.1 g/cm^3 for the four species. The statistical analysis of ANOVA indicated that there is no significant difference of density among trees within and between species (P <0.05).

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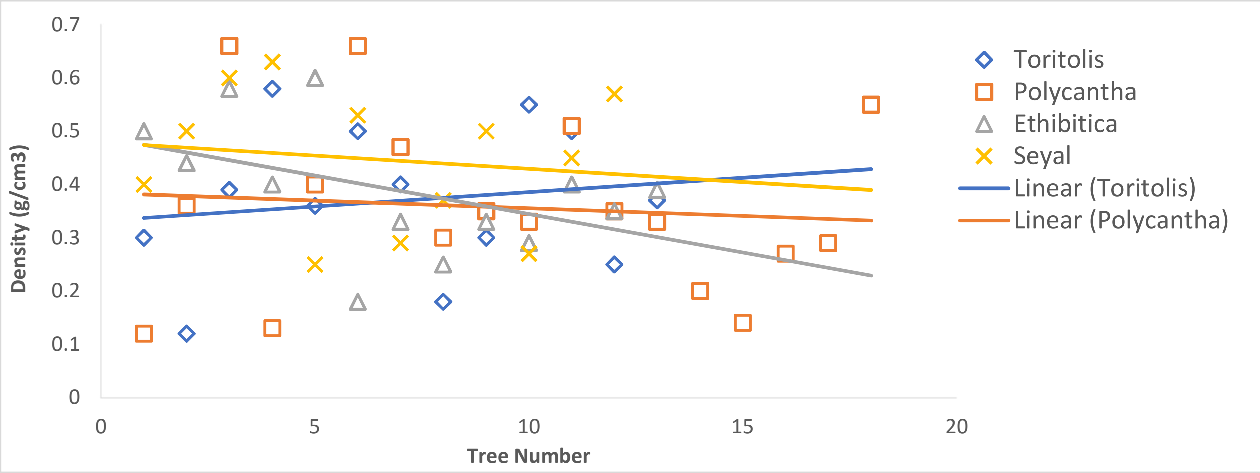

Figure 2. The scattered diagram of mean density wood for the four *Acacia species*

3.1. Untrimmed small branch dry biomass

Untrimmed small branch biomass was determined based on the allometric equation using basal diameters (diameter measured at the bases of the branches) and trimmed (aliquot) biomass of the small branch for each species. Regression analysis was used to develop the model. Using the model predicted dry biomass of the untrimmed small branches and their basal diameter showed a strong relation for each species. The p-value was statistically significant (P-value < 0.01) indicated that, there is a strong evidence that the existence of statistically significant correlation between the independent variable (DBH) and dependent variable (dry biomass of trimmed small branch) and the basal diameter coefficient is reliable estimate of the model. The Adjusted R-squared value >= 0.80, shows that 85% of variance of the output variable (dry biomass trimmed small branch) is explained by the variance of the input variable (DBH branch) for each *Acacia* species (Table 3)

Table 3. Allometric models for determining untrimmed dry branches of the four species

Species	Model	R^2	P-Values
Acacia seyal	y=54.355 + 5.6913(DBHb)	0.85	0.000234<0.01
Acacia polycantha	Y=39.553+3.6976(DBHb)	0.87	0.00294 <0.01
Acacia ethibcia	74.384+5.5975(DBHb)	0.80	0.000324<0.01
Acacia toritolis	y=23.97+7.4463(DBHb)	0.78	0.002756<0.01

DBHb= diameter measured at the bases of the branches

3.2. Dry biomass of the large branches and the trunks ($B_{drysection}$)

The Dry biomass of larger branch and trunk ($B_{dry\ section}$) of *Acacia seyal* has a mean value of 50.02 kg. Likewise, the dry section of *Acacia polycantha, Acacia ethbicia* and *Acacia toritolis* had a mean value of 74.13, 59.64 and 67.30 kg, respectively. *Acacia polyacantha* has large number of branch and stem size as a result it is higher dry biomass as compared with the three of species *Acacia* species. The total dry biomass of the trees for each species was obtained by the sum of the trimmed dry biomass and the untrimmed dry biomass. The mean dry biomass for *Acacia seyal*, *Acacia polycantha*, *Acacia ethbicia* and *Acacia toritolis* is 51.55 kg, 75.38 kg, 61.08 kg, 68.96 kg, respectively (Table 4).

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Table 4. Total dry biomass and component biomass for different Acacia species

species	Tree Component	max	min	mean
Acacia seyal	Dry Section (untrimmed large branch and trunk) ---A	112.02	20.81	50.02
	Dry biomass Branch Untrimmed-----B	2.49	0.55	1.266
	Dry biomass Trimmed branch------C	0 .14	0.38	0 .22
	Total Dry biomass=A+B+C			51.55
Acacia polyacantha	Dry Section (untrimmed large branch and trunk) ----A	112.31	33.42	74.13
	Dry biomass small Branch Untrimmed-------B	1.9	0.2	1.10
	Dry biomass Trimmed branch------C	0 .28	0.04	0.155
	Total Dry biomass=A+B+C			75.38
Acacia ethibcia	Dry Section (untrimmed large branch and trunk) ----A	101.55	35.16	59.64
	Dry biomass Branch Untrimmed------B	0.54	2.39	1.3
	Dry biomass Trimmed branch------C	0.22	0.381	0.144
	Total Dry biomass=A+B+C			61.084
Acacia toritolis	Dry Section (untrimmed large branch and trunk) ----A	136.95	14.2	67.30
	Dry biomass Branch Untrimmed------B	2.3	0.40	1.41
	Dry biomass Trimmed branch------C	0.408	0.105	0.25
	Total Dry biomass=A+B+C			68.96

3.3. Allometric biomass model development

The study has been developed four best models for each species of above ground biomass (AGB) with total of 24 different models were developed by employing independent variables DBH, height, density and their combination as independent variable. Six candidate models were produced for each species. Equation performance analysis of the candidate models were carried out using various goodness-of-fit statistics, namely Akaike's Information Criteria (AIC), residual standard error (RSE) [31, 32, 35-37]. The best equation should have the lowest AIC, RSE and P values and highest R^2.

3.3.1. *Acacia seyal* model

The best preformed regression model to predict the aboveground biomass (AGB) of *Acacia seyal* l is given as Ln (AGB) =2.20636+0.53167ln (DBH^2) $H\varrho$. Based on goodness of fit statistics, its R^2 is highest and AIC and RSE are lower. The overall adjusted R^2 of *Acacia seyal* biomass model is 0.90 indicating that 90% of aboveground biomass is explained by the input variable ((DBH^2) $H\varrho$) and the P-value of the predictor (DBH^2) $H\varrho$) is 4.745e-05< 0.05. This shows that there is strong evidence that supports existence of statistically significant correlation between (DBH^2) $H\varrho$) and AGB as compared other impute variable (Table 5).

Table 5. Summary of statistical indictors, RSE, AIC, adjusted R^2, and p-values for AGB models *Acacia seyal*

Models	Allometric equation	RSE	AIC	R^2	p-value
M1-S	Ln(AGB)= 0.1406+0.8952ln(DBH)	0.262	5.7226	0.69	0.00047
M2-S	Ln(AGB)= 0.2334+1.7039ln(H)	0.35337	12.9013	0.45	0.01078
M3-S	Ln(AGB)=5.5860+1.2317ln(DBH)- 0.00173(H)	0.27619	7.72222	0.75	0.00316

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M4-S	Ln(AGB)=4.9496+1.1740ln(Density)	0.28819	8.00732	0.63	0.00125
M5-S	Ln(AGB)=0.5462+0.9678ln(DBH-0.04911ln(H)+1.8548ln(Density)	0.21359	2.14011	0.8	0.0011
M6-S	(AGB)= 0.20636*((DBH^2)Hϱ) $^{0.53167}$	0.20952	0.35643	0.9	4.75E-05

3.3.2. *Acacia polyacantha* model

The best performance model for the *A. polycantha* is ln(AGB)=2.95854+0.21750ln((DBH)^{2}Hϱ). The corresponding P-value of the model is 1.142 *10^{-11} at confidence interval of 95% i.e. 95% sure that the true relationship between the independent (DBH)^{2}Hϱ and dependent (AGB) lies in the given intervals with probability of error less than 5%. The Adjusted R-squared is 0.94, which explained that, the input variables DBH)^{2}Hϱ) are 94% reliable in explaining the aboveground biomass. The rest, 6% of the variability of the AGB is explained by other factors. In this model the DBH)^{2}Hϱ) is significant predictor of the dependent variable with P-value of 1.142 *10^{-11} which showed that DBH)^{2}Hϱ) is more than 94.4% significant predicting variable in this model (**Table 6**).

Table 6. Summary of statistical indictors, RSE, AIC adjusted R^2, and P-values for AGB models *Acacia polyacantha*

Models	Allometric equation	**RSE**	**AIC**	R^2	p-value
M11_P	Ln(AGB)= 1.55302+0.61960ln(DBH)	0.10236	27.0887	0.8823	4.69E-09
M12_P	Ln(AGB)= 2.2848+0.7946ln(H)	0.18101	-6.5686	0.632	4.90E-05
M13_P	Ln(AGB)= 3.13455+0.48613ln(DBH)+ 0.233817ln(H)	0.0829	-33.842	0.885	3.51E-08
M14_P	Ln(AGB)= 3.176813+0.42240 ln(DBH)+ 0.25075ln(H)+ 0.1316664ln(ϱ)	-24.872	0.10054	0.87	3.04E-07
M15_P	Ln(AGB)= 4.90806+0.52357ln(ϱ)	0.14086	-18.001	0.805	2.77E-07
M16_P	AGB=7.26982((DBH)^{2}Hϱ)$^{0.21750}$	0.0704	-40.565	0.9443	1.14E-110

3.3.3. *Acacia ethibicia* model

The linear multiple regression for *Acacia ethibicia* allometry, resulted an equation of the form, AGB=-AGB= 29.01898*((DBH)^{2}Hϱ)$^{0.21518}$. The relevant statistical outputs were, adjusted R^2 of 0.953 accounted for the explanation of 95.3% of the variance of AGB by the three independent variables. A statistically significant p-value of 13.57*10^{-08} was also acquired (Table 7).

Table 7. Summary of statistical indictors, RSE, AIC adjusted R^2, and p-values for AGB models *Acacia Ethibicia*

Models	Allometric equation	**RSE**	**AIC**	R^2	p-value
M17_E	ln(AGB)=1.03252+0.70011ln(DBH)	-18.928	0.09382	0.93	1.52E-07
M18_E	Ln(AGB)=1.4052+1.0416ln(H)	0.13092	-10.93	0.8779	4.36E-06
M19_E	Ln(AGB)= 1.01523+0.45626ln(DBH)+ 0.42080ln(H)	0.06721	-26.197	0.9278	7.80E-08

M20_E	Ln(AGB)= 1.30413+0.39911ln(DBH)+ 0.43549ln(H)+ 0.07386ln(ϱ)	-25.213	0.07128	0.9467	8.35E-07
M21_E	Ln(AGB)= 4.8399+0.7311ln(ϱ)	0.24185	2.53609	0.6249	0.00134
M22_E	AGB= 29.01898*((DBH)^{2}Hϱ)$^{0.21518}$	-22.387	0.08122	0.953	3.57E-08

3.3.4. *Acacia toritolis* model

In the same way, linear multiple regression analysis of *Maytenus arbutifolia* revealed an equation of the form AGB = 3.82427*((DBH)^{2}Hϱ)$^{0.26748}$. The model 28_T had an adjusted R2 of 0.963, indicating the accuracy of the model, capable of explaining 96.3% variation of ABG by the three independent variables. Statistically significant p-value of 1.702 x10-09 was also obtained.

Table 8. Summary of statistical indictors, RSE, AIC adjusted R^2, and p-values for AGB models *Acacia toritolis*

Models	Allometric equation	**RSE**	**AIC**	R^2	p-value
M23_T	ln(AGB)= 1.85387+0.57421 ln(DBH)	0.11978	-13.064	0.8688	6.26E-06
M24_T	Ln(AGB)= 2.1795+0.8391ln(H)	0.1642	-5.4936	0.7535	0.0001543
M25_T	Ln(AGB)= 1.01523+0.45626ln(DBH)+ 0.42080ln(H)	0.06721	-26.197	0.9078	7.80E-08
M26_T	Ln(AGB)= 1.30413+0.39911ln(DBH)+ 0.43549ln(H)+ 0.07386ln(ϱ)	-25.213	0.07128	0.9167	8.35E-07
M27_T	Ln(AGB)= 4.8399+0.7311ln(ϱ)	0.24185	2.53609	0.6249	0.001343
M28_T	AGB = 3.82427*((DBH)^{2}Hϱ)$^{0.16748}$	0.10529	-16.158	0.963	1.70E-09

3.4. Quantitative statistics

There have been also applied quantitative methods model performance analyses, using various goodness of statistics that quantify the performance of the models. These can be error index and model efficiency test (E).

3.4.1. Model prediction efficiency

Nash-Sutcliffe efficiency (NSE) is one of the measures of model performance efficiency (E) that determines the relative magnitude of the residual variance compared to the measured data variance [38]. It indicates the potential of model performance efficiency in estimating biomass; and is computed as equation as follow.

$$NSE = 1 - \left[\frac{\sum_{i=n}^{n}(O_i - P_i)^2}{\sum_{i=n}^{n}(O_i - \bar{O})^2}\right], \quad (13)$$

where O_i is the ith observation for the constituent being evaluated, P_i is the ith predicted value for the constituent being evaluated, $\bar{O}$ is the mean of observed data for the constituent being evaluated, and ‘n’ is the total number of observations.

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NSE ranges between $-\infty$ and 1.0 with NSE value between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance (Table 9). The Nash-Sutcliffe efficiency (NSE) analysis value indicated that approaching to one, the new developed model for the four species is better performance model as compared with others model. The NSE value for A.*Polyacantha*, *A.Toritolis*, *A.Ethibcia*, and *A.Seyal* is 0.98, 0.81, 0.88 and 0.92, respectively.

Table 9. Model prediction efficiency of the four Acacia species.

	Author's Model				
Species	herny	chave2014	chave2005	Brown	New model
A.Polyacantha	0.33	-5418.82	-5619	-9483.87	0.98
A.Toritolis	0.14	-1548.37	-1514.74	-8801.11	0.81
A.Ethibcia	0.94	-2994.47	-3028.61	-12678	0.88
A.Seyal	0.79	-3052.9	-3095.1	-12929.2	0.92

3.4.2. Error index

Several error indices are commonly used in model evaluation for assessing the accuracy of the model [39]. The smaller the error the more accurate the model is, and a value of "0" error indicates a perfect fit [40].

i) Percent bias

Percent bias **(**$\%bias$**)** measures the average tendency of the estimated biomass to be larger or smaller than their observed counterparts [41]. This method is chosen because $\%bias$ has the ability to clearly indicate poor model performance [41]. It is calculated by using in Mandal, Yadav [42] and the corresponding results were presented in table 10 below.

$$\%bias = \frac{\sum_{i=1}^{n}(O_i - P_i) X\ 100}{\sum_{i=1}^{n} O_i}, \tag{14}$$

Table 10. Percent bias

	Model types				
species	new Eqn	Herny	Chave 2014	Chave 2005	Brown 1997
A.Seyal	15.37	91.61	-3684.71	-3659.73	-8100.82
A.Polyacantha	34.43	91.83	-3760.8	-3730.94	-8213.78
A.Ethibcia	26.67	89.45	-3456.65	-3418.56	-8045.67
A.Toritolis	23.45	90.34	-3267.78	-2989.21	-7995.89

The optimal value of $\%bias$ is 0.0, with approaching to zero indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias [41]. According to Chave, Réjou-Méchain [43], Chave, Andalo [9] and Brown [44] overestimated the observed biomass while [45] is overestimated whereas the $\%bias$ of the new equations are close to zero as compare to others model. This indicated that the newly developed models are more accurate estimator of AGB.

4. Discussion

It is true that the development and application of allometric equations is the standard methodology for AGB estimation of trees [9, 46, 47]. The study model actually differs from the common conventional biomass models such as simple linear (AGB = βDBH), simple log linear

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(lnAGB=ln(βDBH)), multiple linear (AGB= βoDBH+ β1H+….) and log multiple linear (ln (AGB) = ln(βo) + β1ln (DBH). This might be because in either case of model representation a combination of DBH, H, ϱ can be fitted either independently or using their compound derivatives ($\varrho(DBH)^2H$, DBH^2H) as a single predictor [48]. Many works on mathematical models for biomass show the superiority of the power function, notably for estimation of the AGB of trees, [10, 49, 50]. This might be because power models show the relative increment between AGB and two or more independent variable [49]. Moreover, Negash, Starr [34]and [Chave, Andalo [9], Chave, Réjou-Méchain [43]] suggested that the power equation using the compound derivatives of DBH, height & wood density as a single predictor is the best for predicting aboveground biomass of trees.

This study illustrates the relationship between the AGB and D^2H, which is derivative of volume of cylinder, (π/4) D^2H. Apparently mass is a product of wood density (ϱ) and volume (D^2H), hence ϱD^2H is expected to be a good predictor of total aboveground biomass. The same findings were noted in other studies [9, 43, 51, 52] . The models developed in this study are suggested to allow a rapid biomass estimation of the *Acacia species* and thus aid in planning for sustainable use of this species.

The models were developed using 54 sample trees of variable size for the four *Acacia* species. This sample looks less in number for model development. However, it is often the availability of species variation in dendrology and the amount of labour and cost requirement. In relation to current study, other biomass studies have also used similar number of trees as compared to the number of trees used for this study. For instance, Ebuy, Lokombe [27] used 12 trees in Yangambi (Democratic Republic of Congo), Brown and Gaston [51] used 8 trees in Rondonia (Brazil) or Deans, Moran [52] used 14 trees in Cameroon to develop site specific biomass equation. Studies in Ethiopia also used small number of sample trees. For instance Fantu, Nuruddin [53] used 20 trees per species to develop allometric equation of the species they studied (*Eucalyptus globules, Ecalyptus grandis, and Eucalyptus saligna*) from central highlands of Ethiopia. Tesfaye [54] used 20 trees per species to develop biomass models of the species he studied from the Chilimo Forest of Ethiopia (*Olea europaea* ssp. *cuspidiata, Olinia rochetiana*, and *Scolopia theifolia*). This researcher had also used 15 trees per species to develop model of *Allophyllus abyssinicus* and *Rhus glutinosa* in the same study area. Cleemput Cleemput, Muys [55] used 8 individuals per species when they developed biomass model for *Grewia bicolor, Euclea shimperi, Otostegia integrifolia* and *Dychrostachys cinerea* in a semi- arid area of the National Regional State of Tigray, Ethiopia. Soromessa Soromessa [17] used 12 individuals per species to develop allometric model for *Juniperus procera* and *Podocarpus falcatus* in Wof-Washa Forest of Ethiopia. Tekle [56] used 7 and 12 trees to develop allometric equation for biomass estimation of *Allophylus abyssinicus* and *Croton macrostachyus* respectively in Arba Gugu Forest, Ethiopia. In contrary, some other authors had used large data set for equation development.

The current study included wood density, to tree height and DBH as the most important predictor of tree biomass which lead a substantial improvement for the biomass estimation of the four *Acacia* species. This might be due to the fact that density (ϱ) is directly proportional to mass (AGB) that makes it more relevant tree parameter to accurately estimate the biomass of trees. In support of our study, some recent studies also revealed the inclusion of wood density in combination with DBH and height to estimate the biomass of trees [9, 43, 47, 52, 57, 58]. In contrary to this study, other studies demonstrated that the use of DBH alone would provide more accurate estimate than using two or more parameters for predicting total AGB [10, 44, 59, 60]. But this is not usual case in the scientific literature and not true practically. Authors such as Vieira, Alves [61] and Picard, Rutishauser [11]

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suggested the addition of tree height parameter in addition to DBH for better accuracy of tree biomass estimation. In line with this, the current study incorporates more than two variables to estimate the biomass of *Acacia* species.

Only few papers are available in Ethiopia [34, 53, 54, 62]. This current study generally showed the tendency of the overestimation the AGB when the generalized equations are used as compared to the available site-specific equations. This finding coincides with the finding of Wondrade N [62] who compared AGB of *Croton macrostachyus* and *Cupressus lucitanica* using local species specific equations developed by Abate [63] and pantropic general allometric equations of Brown [44] and Chave, Andalo [9] in the Lake Hawassa Watershed, Ethiopia. Among the generalized equations are more inappropriate to estimate the biomass of Acacia species. A possible explanation for higher prediction when applying the generalized model to the current data is probably the deference in wood density and tree architecture. It is evident that Both Brown's and Chave's model, data were not collected from anywhere in Ethiopia. Similar findings were noted by Nigatu Wondrade [62] and Vieilledent [64] who compared brown and Chave equation to the Lake Hawassa Watershed vegetation (Ethiopia) and Madagascar moist trees respectively. Soromessa [17] Also supported the overestimation of biomass when Brown equation was applied to their observed data of *Juniperus procera* and *Podocarpus falcatus.* Similarly, when the equations of Chave, Andalo [9] and Brown [44] were applied to the data of Indonesian tropical lowland Dipterocarp forests, the predicted values were overestimated [65], and the prediction were remarkably overestimated when the Brown was applied. From such analysis, the research finding realizes that the selection of an allometric model is the most important source of uncertainty when assessing tree AGB.

This study revealed that the Brown, chave models were found highly biased estimate even much higher than Herny estimates. This might be because many of data are beyond the data range used in the model (DBH variation) and agro climatic variation. Similar findings was also noted in who reported biased estimate of biomass in the continental tropics when they applied DBH data beyond the allometric domain [66]. This study generally confirmed the importance of local allometry for the better estimation of AGB of *Acacia* species rather than using pantropic equation.

3. Conclusion

The study has offered models for estimating above ground biomass of selected four *acacia species*, which are one of the most common woody plants in Omo gibe woodland in Southwest Ethiopia. Many researches have been done in Ethiopia on carbon sequestration but the capability use of site-specific model is low and use pantropic allometric model. This is result uncertainty and variation of the biomass estimation. Therefore, these models would contribute to significantly improve the accurate estimate of biomass and carbon sequestration of tree in Omo Gibe woodland. Moreover, it is also crucial for monitoring, reporting and verification (MRV) component of REDD+ that provide reliable information of forest carbon stock so as obtain finical rewards for the amount of carbon sequestrated under any possible trading system that may be established. In addition, the model development procedures provide an ideal opportunity for further model development work southwest forest of Ethiopia and elsewhere.

The use of DBH, height and wood density in a combination as predictor independent variables might have made the equation more accurate. Combination of the variables, $(DBH^2)H\varrho$, were the best performing model for Predicting total biomass of the species. The best biomass model for *Acacia syal* and *Acacia polyacantha* is $0.20636*((DBH^2)H\varrho)^{0.53167}$ and $7.26982((DBH)^2H\varrho)^{0.21750}$, respectively. For

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Acacia ethibcia and *Acacia toritolis* best biomass model is $29.01898*((DBH)^2H\varrho)^{0.21518}$ and $3.82427*((DBH)^2H\varrho)^{0.16748}$, respectively. The validation test found out that overestimation of the observed biomass as compared to Brown and Chave general allometric equation. However, the models were statistically more efficient and more accurate to estimate the biomass of the studied species. Results obtained in this study show the necessity of developing specific biomass models for each species, forest type as a country as whole.

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Ethical clearance: There are no plants, animals and human involved for experimental purpose. Therefore, the research is respected environmental rules and regulations.

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