Allometric Equations For Ethiopian Acacia Species

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Allometric equations for Ethiopian Acacia species

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Abstract

Background: Allometric equations are used to estimate biomass and carbon stock of forest. In Ethiopia, despite the presence of large flora diversity, only a few site-specific allometric equations are developed so far. This study was conducted in the Omo-Gibe woodland of south-western Ethiopia to develop an allometric equation to estimate the Above-ground Biomass (AGB) of the four *Acacia* species (*Acacia polyacantha*, *Acacia seyal*, *Acacia etbaica* and *Acacia tortilis*). Fifty-four (54) *acacia* trees were sampled and measured within 35 temporarily established square plots. In each plot, dendrometric variables were measured to derive the models based on combinations of Diameter Breast Height (DBH), height, and wood density as predictor variables. Model performance was evaluated using goodness-of-fit statistics. The biomass was compared using four allometric biomass models that have been widely used in the tropics.

Result: The model containing DBH alone was more accurate to estimate AGB compared to the use of multiple predictor variables. This study, therefore, substantiated the importance of site-specific allometric equations in estimating AGB of *Acacia* woodlands. This is because a site-specific allometric equation recognizes the environmental factors, vegetation types and management practices.

Conclusion: The results of this study contribute to a better understanding of allometric equations and an accurate estimate of AGB of *Acacia* woodlands in Ethiopia and similar ecosystems elsewhere.

Keywords: Above ground biomass, *Acacia* species, Allometric biomass equation, Carbon stock, Omo Gibe woodland

Background

Allometric equations are widely used to estimate forest carbon stocks(C) [1]. Accurate measurement of biomass is crucial for the assessment of carbon stock toward understanding carbon

variations in response to world climate changes [2], monitoring ecological processes such as wood production and nutrient cycling [3] and sustainable management of forest [4].

Currently, various mechanisms have been proposed by the United Nations Framework Convention on Climate Change (UNFCCC) to reducing carbon emissions for climate change adaptation and mitigation. The major climate mitigation option is Reducing Emissions from Deforestation and Degradation (REDD⁺) by promoting conservation, sustainable management of forests, and enhancing forest carbon stocks in the developing countries [5]. One of the critical elements for the REDD⁺ mechanism is the capacity to know the carbon storage potential of forest ecosystems [6]. This can be achieved by establishing biomass allometric equations to reduce uncertainties in carbon accounting and carbon trading in the voluntary and mandatory markets [7, 8].

Different methods, ranging from the most generic to the site and species-specific allometric equations are available for estimating biomass of a tree [9]. Although the general allometric equations are used widely, they may not be able to predict local biomass accurately due to differences in the tree architecture (e.g. several stems, height to branching, etc.), age, diameter, stand density, cultivars, site conditions (climate and soils), and management practices [10]. For example, pruning and coppicing can affect the rate of biomass accumulation [11] as well as the change in biomass without changing the diameter at breast height (DBH) [12, 13]. The general model has shown a large prediction error based on the finding of Mugasha, Eid [14] and Kachamba, Eid [15] in miombo woodlands, Tesfaye, Bravo-Oviedo [16] and Ubuy, Eid [17] in dry forests, and Lisboa, Guedes [18] in moist forests. Therefore, such generic equations may show a systematic error of up to 400 % at the site level [13].

Site specific models provide less bias than general models [19] because the local climatic, soil properties, altitude, and land-use history are affected by tree growth characteristics [20]. According to Mokria, Mekuria [21], the lack of a site-specific allometric model for estimation of AGB is the key reason for persistent inaccuracy and low uncertainty in biomass estimation in sub-Saharan Africa. Solomon, Birhane [22] stated that the precise estimation of biomass and carbon stock in a forest can be achieved using site-specific allometric equations for the species and forest types.

According to Henry, Picard [23], reviews of biomass models in sub-Saharan Africa, 63 models have been developed in Ethiopia, which focused only on six allometric equations, of which 70% of the models were developed for eucalypt species [24]. However, following the review of Henry, Picard [23], there have been attempts to develop local species-specific allometric equations for

estimating AGB of trees in different parts of Ethiopia in recent studies [24], such as Tesfaye, Bravo-Oviedo [16], Kebede and Soromessa [25], Daba and Soromessa [26] and Daba and Soromessa [27] but still, they are not sufficient in respect of vegetation types and agro-ecology of Ethiopia.

Most of the previously developed allometric equations were based on the destructive method, which is costly and time-consuming to implement in wide strata of a forest area [28]. According to Henry, Picard [23], the allometric equations in Ethiopia are developed based on a destructive sampling method, which does not obey environmental principles and is not feasible in the large-scale analysis [28]. There are also cultural, legal and policy aspects of applying the destructive method for tree sampling. In Ethiopia, the national legislation does not allow logging activities of the indigenous trees. According to Tesfaye, Bravo-Oviedo [16] cutting down an indigenous tree is prohibited by law, and this made it difficult to develop biomass allometric equations for the species.

Recently, a semi-destructive method has been explored using Picard, Saint-André [29] and satellite data [30] procedure. The semi-destructive method can also help for easy measurement of the parameters without cutting the tree. Therefore, the semi-destructive sampling method was used for modeling AGB of the indigenous trees, apply in degraded woodland and important in key conservation areas where cutting is prohibited [30]. Publications on semi-destructive methods have been increasing in recent year in Ethiopia including the work of Worku and Soromessa [31] in Wof-Washa dry Afromontane forest, Daba and Soromessa [27],[26], in Biosphere Reserve forest of southwestern Ethiopia and Kebede and Soromessa [25] in Mana Angetu moist Afromontane forest of Ethiopia and Mahmood, Siddique [32] in Hill zone of Bangladesh.

In Ethiopia, several forest resource assessment campaigns have been undertaken to understand the AGB status and management options of the forest resources [33]. However, achieving high-level accuracy of these assessments estimation remains to be challenging [21]. This is partly because of a high level of uncertainty emanating from the nature of the allometric models used for biomass determination. Measurement errors and sample sizes are also major sources of uncertainty in the AGB assessment efforts [34, 35]. It is clear that site- and species-specific models need to be developed and the suitability of the existing allometric equations needs to be evaluated to make accurate biomass assessment and make an informed decision While several allometric equations are claimed to be suitable for ‘tropical forests. However, tropical forests are highly diverse in their

ecology and vegetation composition, ranging from moist high forests to woodlands in arid climates. The high biological diversity of tropical forests also makes it difficult to use a ‘one-fits-all’ model. Particularly the *Acacia* woodlands, which are ecologically and economical of high value in Ethiopia, are given little research attention from point of view of developing allometric models that are suitable for accurate forest biomass assessments.

Acacia woodland is an iconic ecosystem in Ethiopia, accounting for 11% dry land woodland of the country [36]. In this case, Woodland is defined as the type of land cover characterized by trees and shrubs with a tree crown cover of 5–10% of trees able to reach a height of 5 meters at maturity and a crown cover of more than 10% of trees not able to reach a height of 5 meters at maturity, having less diversify species [37]. More than 58 *Acacia* species are known to occur in Ethiopia, of which 49 are indigenous [38] and six of these are threatened species [39]. *Acacia* is widely distributed in the Omo Gibe valley of Ethiopia [40] and it provides paramount ecosystem services values, including food and habitats for a variety of animals, from hoofed mammals and birds to countless species of insects [41], nitrogen-fixing, and hydrological regulation.

Therefore, this research was set out to develop a species-specific biomass allometric equation for estimating the AGB of the *Acacia* species in the woodland of Omo Gibe valley in Ethiopia. In so doing, the study contributes to the reliable estimate of AGB in the woodland ecosystems and contributes to informing decisions on woodland management and carbon accounting, further facilitating carbon trading and global climate change mitigation. The objectives of the study were, therefore, to: (1) derive and evaluate AGB models for the *Acacia* species in Omo Gibe valley, and (2) to compare performances of the widely used biomass equations in estimating biomass of *Acacia* woodland.

Methods

The study area

The Omo-Gibe woodland is located in the Omo gibe Basin, part of central highlands Ethiopia and 210 km away from Addis Ababa, the capital city of Ethiopia. The geographical bound of the area is within the coordinates of 037°40’- 038°10’ longitude E and 07°50’- 08°20’N latitude (Figure 1). It is situated in the headwaters of the Om-Gibe basin which is one of the most important river basins in the country. The elevation ranges between 1,096 m and 2,153 m, and the mean altitude is 1,735 m. The area is characterized by a wide range of topographic features, ranging from deep gorges (faults), through dissected ridges to undulating plateaus. Due to the altitudinal differences,

there is a large variation in rainfall and temperature year to year in the study area [42]. The rainfall increases with altitude but temperature decreases [43]. Based on Ethiopian Meteorological Agency (EMA) data analysis, the annual average rainfall varies from 856 mm to 1,600 mm, with a bimodal distribution that allows two growing seasons [43, 44]. The main rainy season (monsoon rains) extend from June to September and the short season (Belg rains) fall between March and April. The mean minimum and maximum temperatures are 12.7 °C and 26.7 °C, respectively. The *Acacia* woodland of the Omo Gibe valley covers about 3,179,060 ha (40.02%) of the total land area [45]. The dominant species are *Acacia senegal* (Linn.) Willd., *Acacia seyal* (Del.), *Acacia tortilis* (Forssk.), *Acacia polyacantha* (Willd.), *Acacia etbaica* (Schweinf.), *Acacia mellifera* (Vahl) Benth, *Commiphora africana* (A. Rich.) Engl., *Commiphora myrrha* (Nees) Engl., *Cordia monoica* (C. ovalis), and *Commiphora boranensis* (Voll). The area is among the most densely populated areas of the country, (283 person per square kilometre) and the major economic source is agricultural activities [40].

Biomass data collection method

A forest inventory was carried on 35 temporarily established plots (50 × 50 meters) using a systematic random sampling procedure. *Acacia* species were identified in the field using the tree identification manual developed by Bekele-Tesemma and Tengnäs [46] and with the assistance of a skilled botanist. The samples were established based on the Nyman optimal allocation formula [47]. All trees with DBH >10 cm within each plot were identified and DBH measurement of these trees was undertaken. Trees were stratified into 6 DBH classes for biomass analysis (Table 1): < 20, 20.1 – 30, 30.1–40, 40.1 – 50, 50.1–62.1, and > 62.1 cm. For the AGB model development, from each DBH class, two individual tree samples were taken from the three *Acacia* species (*Acacia seyal*, *Acacia tortilis*, *Acacia etbaica*) (6 DBH classes × 2 trees × 3 species = 36 samples), and three tree samples were taken from *Acacia polyacantha* (6 DBH classes × 3 trees × 1 species = 18samples). In total, 54 tree samples were selected and tagged properly. In case a plot is more diverse than others, we took two samples. In each sampling plot, DBH (cm) above ground from the uphill side of the standing tree was measured using a caliper and the total height of the tree was measured by climbing up at the top of the tree using a measuring tape. Moreover, the diameter and height of the untrimmed branches were measured in the field. Also, fresh biomass of trimmed small branches and leaves were measured in the field before sending the samples to the laboratory. The trimmed small branches and untrimmed branches were differentiated based on their diameter:

trimmed small branches are those that have diameter < 10 cm and these were harvested (trimmed) for the analysis in the laboratory whereas untrimmed branch diameter >10 cm. Moreover, counting of the number of a large and small branch in the standing marked tree was undertaken for later calculation of biomass for each of the components.

Biomass calculations

The total Above Ground Biomass (AGB) of the standing tree was partitioned into four architectural components to apply the semi-destructive approach. These are dry sections (stem and untrimmed large branch), untrimmed small branch, trimmed small branch (SB), and leaves (Table 2). According to Picard, Saint-André [29], the procedure for obtaining the biomass of stem and the untrimmed large branch is the same. The dry weight of the large branches and stem (Dry section) was obtained by using Equation (1).

$$B_{dry\ section} = \bar{\rho} \times V_i \quad (1)$$

Where, $B_{dry\ section}$ = biomass of the stem and untrimmed large branch, V_i = Volume of section i and $\bar{\rho}$ = density of wood (obtained from the ratio of the biomass of trimmed small branch to its volume, determine in the laboratory).

The volume (m^3) of the stem and untrimmed large branches were calculated (Equation 2) from the cross-sectional measurements using Smalian's formula [48], assuming that each of the measured stem and the large untrimmed branches was a cylindrical shape. The stem and the untrimmed large branches in each tree were subdivided in the section at the intervals of 2 m distance and the top end and the lower end of each section interval diameter was measured to obtain the volume of each section. Since the division was short (2 m), the shape of the sections was a bit different from a cone, with very little tapering; thus, volume determination using Somalian's and other formulas may have very slight differences [29]. Therefore, sum up the volume of all section (2 m interval having top and lower diameter measurement) divided by the number of the section volume measurement in the trunk and untrimmed large branch was provided with the total volume of the stem and untrimmed large branch (dry section).

$$V_i = \frac{\pi}{8} Li(D_{li}^2 + D_{2i}^2) \quad (2)$$

Where, V_i = the volume of section i , Li is its length of the trunk and untrimmed large branch (m), and D_{li} and D_{2i} are the diameters (cm) of the two extremities of section i . (i.e., D_{li} = diameter of the narrow end of the trunk (cm) and D_{2i} = diameter of the large end of the trunk (cm))

Biomass of untrimmed small branch

The untrimmed branches are those that have diameter >10 cm and these were not cut down in a standing tree. The biomass of the untrimmed small branch was calculated using a linear regression equation between the diameter of the untrimmed small branch and biomass of the trimmed small branch (Equation 3). The linear relationship was first established based on biomass measurements from trimmed small branches and the corresponding diameter of the untrimmed small branch. We then used the parameter estimates from the linear regression and used to estimate the untrimmed small branch biomass. To determine the total biomass of untrimmed small branches per tree, the calculated biomass of the untrimmed small branch was multiplied by the number of untrimmed small branches.

$$B_{\text{untrimmed biomass small branch}} = a + bD \quad (3)$$

Where, the B is the biomass of the untrimmed small branches and D is the untrimmed diameter of the small branch (measured), a, b are model parameters (intercept and slope, respectively).

Biomass of trimmed small branch and leaves

The small branches of trees were trimmed using the local machete and the twigs and attached foliage were carefully separated from each trimmed small branch. Two small branches were trimmed for sampling from each tree for laboratory analysis. To determine the fresh weight of the trimmed small branch (wood aliquot) and leaves of each compartment, their biomass was measured using a spring hanging weighing scale of 5 kg capacity (0.02 kg precision).

The total biomass of the trimmed small branches was obtained from the number of small branches in the standing tree multiplied by the average biomass of the trimmed branch. Similarly, to obtain the total biomass of the leaves of a tree, the average leave biomass was multiplied by the total number of small branches per tree.

Laboratory analysis

Fresh sub-samples of 200-250 g for trimmed small branch and 150 g for leaves of each marking trees were transported to the laboratory to determine the moisture content, wood density and volume the trimmed components. For wood density (g/cm³) and volume (cm³) analysis, disc samples were cut using a hand saw from each of complete trimmed small branches, and fresh weights of these samples were measured using spring hanging. The total number of discs was 72: two discs per species (36 for *Acacia polyacantha* and 36 discs for the three species altogether (*Acacia seyal*, *Acacia etbaica*, *Acacia tortilis*)) and Wolkite University laboratory was used for the analysis. Wood aliquot volume was determined using the water displacement method, as outlined

in Vieilledent, Vaudry [49]. The aliquots were then oven-dried (105 °C for 72 hrs.) to determine the moisture content. The determination of wood density for each i^{th} discs collected from the j^{th} sampled trees was estimated from the ratio of oven-dry weight (g) and volume (cm^3). The mean wood density (ρ) for each tree was computed using Equation 4.

$$\rho = \sum_{j=1}^{j=72} \rho_j / n \quad (4)$$

Where n = the number of samples, j = disc samples from 72 trees.

The total AGB (kg/tree) of a standing tree is, therefore, the sum biomass of all components of the tree. That is the sum of the biomass of the dry section, untrimmed small branch, and trimmed small branch and leaves (Table 2).

Construction and evaluation of allometric equations

Before establishing the allometric equation, data were evaluated for outliers and then the sources of these outliers were investigated. Eventually, measurement errors were detected to be the source of the outlier data. The outliers were, therefore, removed and data were collected again to replace the wrong and removed data. Six non-linear regressions were used to test the best-fit model for the total AGB and tree components biomass such as dry section, untrimmed small branch, trimmed small branch and leaves.

The models and the corresponding variables used were: Model 1 (DBH only), Model 2 and 6 (DBH in combination with height), Model 3 (DBH in combination with density of wood), and Model 4 and 5 (DBH combination of H and ρ) (Table 3). The statistical analysis was conducted in R software, using a package of ‘NLS tools’[50].

Model diagnostics were performed using goodness-of-fit statistics, namely, Corrected Akaike Information Criterion (AICC) (Equation 5), Root means square error (RMSE) (Equation (8)), and Residual Standard Error (RSE)[51]. The best species-specific biomass allometric equation showed the lowest AICC and Residual Standard Error (RSE) [15]. Based on these diagnostics, the models were ranked (1 to 6) according to each goodness-of-fit statistic [52]. The RMPE and MPE were conducted in excel using the corresponding equations 6 and 7, respectively, which were used to show the model performance. All the advanced statistical analyses such as AIC and RSE were done using R software.

Model validation was carried out using the leave-one-out cross-validation (LOOCV) procedure [53] and results assessed using the adjusted coefficient of determination (R^2_{adj}) and Root Mean Square Error (RMSE) statistics, using equations 8 & 9. The LOOCV followed the algorithm as

reported by Ji, Wylie [54]. A single plot was withheld as a validation sample and the remaining plots were used to train the models. The advantage of LOOCV technique is providing an unbiased estimation of the prediction error and to increase the robustness in the results[55].

$$AICC = n \log \left(\sum_{i=1}^n \frac{(AGB_{est,i} - AGB_{obs,i})^2}{n} \right) + 2p \quad (5)$$

$$RMPE = \sum_{i=1}^n \frac{MPE}{Y} \times 100 \quad (6)$$

$$MPE = \frac{(AGB_{est,i} - AGB_{obs,i})}{n} \quad (7)$$

$$RMSE_i = \sqrt{\frac{\sum_{j=1}^n (obs_{,i} - mean\ est_{,i})^2}{n}} \quad (8)$$

$$R^2 Adj = \frac{1 - \sum (obs_{,i} - mean\ est_{,i})^2}{\sum (obs_{,i} - mean\ est_{,i})^2} \quad (9)$$

Where, AIC (unitless) = Akaike's information criterion, RMPE = Relative mean prediction error (%), RMSE= Root mean square error, MPE = Mean prediction error (%), R^2 = Adjusted coefficient of determination, $AGB_{est,i}$ = Predicted AGB and $AGB_{obs,i}$ = Observed total AGB of individually measured tree i and Y = the average of observed total AGB (kg/ tree), n= the total number of sampled trees, and p = the number of parameters in the tested model.

Comparison of biomass allometric equation

A comparison of the allometric equation was undertaken to estimate AGB (Table 4). A large number of regression models have already been published; however, this study focused on four equations, which are widely used in Ethiopia for biomass assessment. The four equations we considered in our comparisons are Brown [56] allometric equation, which was developed based on data from the moist tropical forest; Henry, Picard [23], who used data from the dry land forest of East Africa; Chave, Réjou-Méchain [13], using data from the tropical dry forest and Guedes, Siteo [57] from the dry land ecosystem in Mozambique. We compared the performance and validity of the allometric equations developed in Omo Gibe woodland comparing with the four published allometric equations using MPE and RMPE [58]. For validation, the AGB collected in the field (observed) and the predicted biomass using the existed allometric equations were used.

Results

Tree density

To understand the AGB per hectare, tree density (number of trees per unit area of land) analysis was conducted and accordingly, *Acacia polyacantha* was found to have higher tree density

(261±2.3 trees/ha), followed by *Acacia seyal* (191±1.5 trees/ha) and *Acacia etbaica* (178±1.2 trees/ha). The *Acacia tortilis* was found to be of lower tree density (156±1.1 trees/ha) (Table 1).

AGB estimates and models

The observed mean AGB in the Omo Gibe woodland was 2397±192 kg/tree. The mean AGB for *Acacia polyacantha*, *Acacia tortilis*, *Acacia etbaica* and *Acacia seyal* was 2804±165 kg/tree, 2326±154 kg/tree, 2087±133 kg/tree, and 2111±142 kg/tree, respectively (Table S1). Based on goodness-of-fit statistics and LOOCV analysis, the model based on DBH alone ($y=\alpha\text{DBH}^\beta$ in model 1) provided the best fit for AGB estimation. Across all equations, the parameter β_1 describing the influence of DBH, was statistically significant ($p=0.0041$) in each model. Similarly, the model parameter β_2 describing the influence of height was also statistically significant ($p=0.0053$). The parameter β_3 , showing the influence of wood density, however, was not significant ($p=0.0072$) (Table S2).

The AGB of each tree component expressed as a function of DBH only in model 1 had a lower AIC (494) and RSE (52 kg/tree), which indicates that a very good performance of the model. The performance of Model 2 in estimating AGB was shown to be second to that of Model 1 and the influence of DBH and height in predicting AGB (parameters β_1 and β_2) were significant ($p=0.0076$), with AIC and RSE values of 501 and 61 kg/tree, respectively, (Table S2). Model 6 ranking third, having AIC and RSE values of 525 and 74 kg/tree, respectively. Model parameter β_3 was, however, non-significant ($p=0.182$). Models 4 and 5 had approximate AIC and RSE values and ranked the fourth and fifth, respectively; model 3 had the highest AIC and RSE, ranking 6th. The model parameter of wood density (β_2) was non-significant ($p=0.063$); adding wood density as a predictor variable in the model with a combination of DBH and height did not improve the performance of the models. Correlation analysis of predictor variables shows that there is a strong relationship between DBH and tree height ($R^2=0.87$, $r=0.83$) (Figure 2a) and volume ($R^2=0.83$, $r=0.77$) of the trees (Figure 2b).

The LOOCV validations among the six evaluated models confirm that the similarity and highly reliable relationships between predicted and observed data for the models, with no substantial trends in the prediction errors. For each model prediction, the cross-validation revealed that the differences between RMSE and RMSE_{cv} are not observed (Table 5). The adjusted R^2 also did not show a significant difference between the normal and the LOOCV analysis of the models.

Comparison of allometric equations

The average AGB estimate based on the equation developed in this study was 2940 ± 195 kg/tree; on the other hand, the estimates based on Henry et al., and Guedes et al., models were 2521 ± 171 kg/tree and 3240 ± 203 kg/tree, respectively. The pan-tropical models developed by Chave, Réjou-Méchain [13] and Brown [56], which are currently being widely used in Ethiopia for biomass and carbon stock assessments, are shown to have a large variability of prediction and overestimating the AGB of *Acacia* woodland in the study area (Figure 3). Statistically, no significant difference ($p=0.0072$) was observed among the AGB estimate based on our model and those based on Henry, Picard [23] and Guedes, Siteo [57]. However, a comparison of our model with that of the Pan-tropical models: Brown [56] and Chave et al.[13], shows a significant difference in AGB estimates (Figure 4).

The comparison of the allometric equations showed a large variation of accuracy in terms of RMPE and MPE. The RMPE and MPE value of the allometric equations developed in this study was 0.06% and 0.26%, respectively. The RMPE and MPE values for [57] and [23] were shown to be close to those calculated for the equations developed in this study (respectively, RMPE and MPE values of 0.08%, and 1.91% for Henry et al. and 0.09% and 2.21% for Guedes et al. The largest RMPE and MPE values were those calculated for Brown⁴⁴ equation (respectively, -1.74% and -83%), and followed by [13] (RMPE and MPE of -1.2 and -60%, respectively). These values were by far higher than the values obtained using the allometric equation developed in this study.

Discussion

In this study, the performance of allometric equations was evaluated using multiple predictor variables (DBH, Height (H) and wood density) in estimating the AGB of a tree in *Acacia* woodland.

In agreement with many similar studies, our findings demonstrated that the use of DBH alone would provide a more accurate estimate of the total AGB than using two or more parameters which is in agreement with many other studies [13, 22, 59, 60]. This is convenient because DBH is a variable that is easily-to-measure, compared to wood density and height. Height and wood density is, perhaps, more prone to measurement errors than DBH, which could influence model performances. Contrary to our findings, several other studies reported that the inclusion of multiple predictors, such as wood density, in combination with DBH and height, provides a better estimate of tree biomass [61-63]. However, due to the time-consuming nature and high cost involved in

measuring height and wood density, the practical applicability of these variables in biomass assessment of a large tract of forest areas could be limited.

The correlations investigated show that AGB was significantly and positively correlated with DBH ($r=0.81$) and height ($r=0.59$) but not with wood density ($r=0.069$) (Table S3). The lack of correlation between the AGB and wood density indicates that wood density does not consider as a potential-dependent variable in the model. Based on the global wood density database, wood density can vary widely among individual trees within a species in a given region [64]. Wood density can vary depending on tree density and environmental factors such as climate, soil type and altitude [57]. Therefore, according to Zanne, Lopez-Gonzalez [64] and Chave, Coomes [65], the wood density ranges from 0.1 to 1.5 g/cm³ among tropical trees and the *Acacia* species wood density in Africa also ranged from 0.48 g/cm³ to 0.826 g/cm³, with an average of 0.612 g/cm³ [66] whereas the study *Acacia* species average wood density was 0.39 g/cm³, ranged from 0.12 to 0.63 g/cm³. Therefore, the model incorporating wood density was rejected since wood density value in this study was the lowest record and it contributed to select the simplest model.

The measurement of DBH in the field, on the other hand, is inexpensive and less time-consuming. In this study, wood density was recognized as a predicting variable to test AGB predictions and tree components. However, it did not improve the performance of models and were not significantly different in the biomass estimation ($p=0.0091$) in all tested models. This is supported by findings from other researches such as that of Lisboa, Guedes [18] and Paul, Roxburgh [67].

The leaf size of the *Acacia* species is very small, compared to many other broad-leaved tree species and, hence it is not expected to have substantial contributions to the total biomass estimation. The moisture content of the leaves is high and the dry weight is understandably low. This implies that the contribution of leaves for the total AGB is minimal which is helpful to select the simplest model in our study area. This is supported by Mate, Johansson [68], the contribution of leaves to the total AGB was only 3% in the Miombo woodlands of Mozambique.

While the biomass estimates based on our equation significantly differed from those based on [56] and [13], possibly, the observed biomass significant differences could arise from the fact that the Omo Gibe *Acacia* woodland ecosystem is different from the Chave et al and Brown models development ecosystem.

[23], on the other hand, developed the model using data from dry forest of East Africa and [57] equations were also developed based on a dry woodland ecosystem in Mozambique. These

ecosystems are more similar to our study area (at least from climate perspectives) than the moist tropical forest studied by Brown⁴⁴ and Chave, Réjou-Méchain [13]. No statistically significant difference ($p > 0.05$) and less error were observed among the allometric model developed in the Omo Gibe woodland and those by Henry, Picard [23] and Guedes, Siteo [57]. Moreover, Henry had taken vegetation data from Ethiopia during model development and Guedes model also used widely in the dryland forest of Africa. The results of RMPE and MPE analysis indicate that the model developed from Mozambique woodlands and East Africa dry forest can predict the AGB in woodlands of Omo Gibe in Ethiopia. This could be due to having a similar agro-ecological zone of the equation's developments.

Soromessa [69] also reported the overestimation of biomass when Brown [56] was applied to their observed data of *Juniperus procera* (Hochst. Ex. Endl.) and *Podocarpus falcatus* (Thunb.) Mirb. in Ethiopia. The findings of Wondrade, Dick [70], and Tesfaye, Bravo-Oviedo [16] are also in agreement with our study. Yet, Chave et al.¹⁵ and Brown⁴⁴ allometric equations are widely used in Ethiopia for carbon stock assessment and they resulted in uncertainty and unreliable estimation of the biomass [70].

The findings from these comparisons imply that the choice of an appropriate allometric equation in a given set of environmental conditions and tree species is essential for accurate estimating AGB of a tree and generating reliable information. Studies also showed that provincial differences in tree diameter and height are important sources of uncertainties in estimating biomass using allometric equations [71]. The sample trees used by Brown [56] and Chave, Réjou-Méchain [13] were, for instance, typically tall trees and large diameter size that may grow much more than 20 meters in the moist evergreen forest, while woodland in Omo Gibe of southwest Ethiopia is dominated by lower height and diameter species, which results in lower AGB for trees in the woodlands. It is also evident that both Brown [56] and Chave, Réjou-Méchain [13] samples data were not collected from within Ethiopian woodland areas. Thus, site-specific models need to be developed to obtain a reliable allometric equation for biomass assessment and carbon stock estimates for use in a wide range of environmental and ecological applications, including REDD+. Hence, the accuracy of carbon sequestration potential estimation for Ethiopian forests using site-specific allometric could be improved if allometric equations are rigorously tested and developed for the major forest ecosystems of the country.

The allometric equation developed in this study could be substantial contribute to efforts being made to improve the accuracy of biomass and carbon sequestration estimates of *Acacia* woodland in Ethiopia. The equation may also be usable in other similar ecosystems elsewhere, particularly in data-scarce regions and where robust allometric equations are lacking. However, the performance of the models in other similar ecosystems of *Acacia* woodland may need to be further tested. Future studies may also consider the influence of environmental variables such as climate and topography on performances of different models and the influence of different predictor variables on AGB.

Conclusion

The study has developed site- and species-specific models for estimating AGB of *Acacia* species in Omo Gibe woodland of Ethiopia. The newly developed models can be of use for generating reliable information on carbon stock estimation and Monitoring, Reporting, and Verification (MRV) component of REDD+ particularly, in *Acacia* woodlands of Ethiopia. The model based on DBH alone as predictor variables and a combination of DBH and H was found to be better performing models in predicting AGB, compared to the other alternative models. The power model with DBH alone was shown to perform best in terms of model performance measurement (AIC, RMSE, RMPE, and MPE). Conversely, the model based on height combined with DBH was found to be the second better predictor variable. Wood density did not improve the performance for all tested models. Therefore, the finding did not encourage the use of multiple predictor variables for the estimation of AGB of *acacia* species. The costs and time involved in measuring several variables are also essential in choosing an appropriate allometric equation. Moreover, the site-specific model is a precise estimator of AGB since it considers the environmental factors and semi-destructive method can apply in the wider area of a forest, degraded land, threaten species and cutting prohibited area of the forest. In sum, our study concludes that the inclusion of multiple predicting variables may not necessarily lead to considerable improvements for predicting the AGB but a single variable such as DBH may provide biomass estimates at a sufficient accuracy level.

Author Contributions

ABA has been collected field data, written the paper as principal. TS has been also modified the method, analysis guide for field data collection. EE interpretation and

designed the study. GL edit and modified the article. All authors read and approved the final manuscript.

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Competing interests

The authors declare no conflict of interest.

Availability of data and materials

All authors declare that the data used in this research are available upon request.

Consent for publication

Not applicable.

Ethics approval and consent to participate

Not applicable.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

Figure 1

The geographic location of Omo Gibe woodland in Ethiopia. The map was produced in ArcGIS Desktop version 10.4 (<https://www.esri.com/en-us/arcgis/products/arcgis-desktop/>). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion

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Figure 2

Diameter relationship with height (a) and volume (b)

Figure 3

Box plot comparison of biomass in the study site and previously published models

Figure 4

Relationships between estimated and measured aboveground biomass of sample trees in tone (t) per a tree ($n = 35$). R^2 , RMPE% and MPE% show error produced in the estimation of the biomass.

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