



# Allometric equation for estimating aboveground biomass of *Acacia-Commiphora* forest, southern Ethiopia

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**Background:** Most of the biomass equations were developed using sample trees collected mainly from pan-tropical and tropical regions that may over- or underestimate biomass. Site-specific models would improve the accuracy of the biomass estimates and enhance the country's measurement, reporting, and verification activities. The aim of the study is to develop site-specific biomass estimation models and validate and evaluate the existing generic models developed for pan-tropical forest and newly developed allometric models. Total of 140 trees was harvested from each diameter class biomass model development. Data was analyzed using SAS procedures. All relevant statistical tests (normality, multicollinearity, and heteroscedasticity) were performed. Data was transformed to logarithmic functions and multiple linear regression techniques were used to develop model to estimate aboveground biomass (AGB). The root mean square error (RMSE) was used for measuring model bias, precision, and accuracy. The coefficient of determination ( $R^2$  and adjusted [adj]- $R^2$ ), the Akaike Information Criterion (AIC) and the Schwarz Bayesian information Criterion was employed to select most appropriate models.

**Results:** For the general total AGB models, adj- $R^2$  ranged from 0.71 to 0.85, and model 9 with diameter at stump height at 10 cm ( $DSH_{10}$ ),  $\rho$  and crown width (CW) as predictor variables, performed best according to RMSE and AIC. For the merchantable stem models, adj- $R^2$  varied from 0.73 to 0.82, and model 8) with combination of  $\rho$ , diameter at breast height and height (H), CW and  $DSH_{10}$  as predictor variables, was best in terms of RMSE and AIC. The results showed that a best-fit model for above-ground biomass of tree components was developed.

$$AGB_{Stem} = \exp \{-1.8296 + 0.4814 \text{ natural logarithm (Ln)} (\rho D^2 H) + 0.1751 \text{ Ln (CW)} + 0.4059 \text{ Ln (DSH}_{30})\}$$

$$AGB_{Branch} = \exp \{-131.6 + 15.0013 \text{ Ln} (\rho D^2 H) + 13.176 \text{ Ln (CW)} + 21.8506 \text{ Ln (DSH}_{30})\}$$

$$AGB_{Foliage} = \exp \{-0.9496 + 0.5282 \text{ Ln (DSH}_{30}) + 2.3492 \text{ Ln} (\rho) + 0.4286 \text{ Ln (CW)}\}$$

$$AGB_{Total} = \exp \{-1.8245 + 1.4358 \text{ Ln (DSH}_{30}) + 1.9921 \text{ Ln} (\rho) + 0.6154 \text{ Ln (CW)}\}$$

**Conclusions:** The results demonstrated that the development of local models derived from an appropriate sample of representative species can greatly improve the estimation of total AGB.

**Keywords:** aboveground biomass, *Acacia-Commiphora*, destructive sampling, local models

## Introduction

The Climate Resilient Green Economy (CRGE) strategy is one of the strategies that Ethiopia has presented to the world community as a model multifaceted development strategy (Federal Democratic Republic of Ethiopia 2011). Among the key values of the CRGE strategy, forests are recognized for their economic and environmental benefits, and the forest sector is one of the four main pillars of the strategy. The major forest biomes of Ethiopia, including

dry evergreen Afromontane, moist evergreen Afromontane, *Combretum-Terminalia* and *Acacia-Commiphora* biomes, host diverse native floral diversity with multiple ecosystem services. At the 17th Conference of the Parties held in Durban in 2011 (COP17), the Ethiopian government introduced a novel development strategy known as a climate-resilient green economy. The country pledges to reduce its greenhouse gas (GHG) emissions by 64% by 2030 through a nationally determined contribution. REDD<sup>+</sup> (Reducing Emissions from Deforestation; Reducing Emis-



sions from Forest Degradation; Conserving Forest Carbon Stocks; Sustainable Management of Forests; Improving Forest Carbon Stocks) has been integrated into this green economic growth model, which will play a significant role in greening the Ethiopian economy. Around 50% of the emission reduction target between 2010 and 2030 will be achieved through measures in the forest sector. The Readiness Preparation Proposal (R-PP 2011) proposed that Ethiopia must establish a measurement, reporting, and verification (MRV) system for GHG emissions, including GHGs from deforestation and forest degradation. To this end, a robust and transparent national forest MRV system must be set up in accordance with the national circumstances and the respective possibilities. The monitoring function (M) of the country's national forest monitoring system will allow us to assess a wide range of forest information, including in the context of REDD<sup>+</sup> and the functions of MRV for REDD<sup>+</sup>. This in turn helps us estimate and report internationally on forest emissions and removals.

Mapping the terrestrial carbon stock is important for the successful implementation of climate protection measures. Tropical forests play a major role in international efforts to mitigate climate change because of their large capacity to store carbon (Gibbs et al. 2007). Allometric equations have been used to predict biomass and productivity of both mixed, multispecies and mature forests, covering a wide range of diameter and height classes (Andersson 1970). To date, several allometric equations have been developed (Basuki et al. 2009; Brown 1997, 2002; Brown et al. 1989; Chave et al. 2005, 2014; Henry et al. 2010; Litton and Kauffman 2008; Mugasha et al. 2013; Nelson et al. 1999; Pilli et al. 2006; Smith 1993; Vieilledent et al. 2012; Whittaker and Woodwell 1968). But in Africa in general, and in Ethiopia in particular, the limited availability of species-specific or mixed allometric equations has led to widespread use of pantropical equations for estimating tree biomass. Most biomass equations have been developed using tree samples collected mainly in pantropical and tropical regions (e.g., Brown 1997; Brown et al. 1989; Chave et al. 2005, 2014). Using generic equations can over- or underestimate biomass and therefore site-specific equations would improve the accuracy of biomass estimates. Site- and species-specific allometric equations use one or more easily measured tree parameters such as diameter, height, and wood density, or a combination thereof (Kangas and Maltamo 2006). This has high potential to increase the accuracy of biomass carbon estimation for financial reward. It also enhances the country's MRV activities.

The current capability of REDD<sup>+</sup> and its performance-based carbon finance schemes involves accurate equations to estimate above- and below-ground biomass and consequently account for carbon stocks and fluxes in different vegetation types in the tropics. However, site-specific biomass equations are missing for most of Ethiopia's vegeta-

tion types. These may over- or underestimate the biomass and carbon stock estimate. In addition, the level of uncertainty associated with previously published pantropical allometric aboveground biomasses (AGBs) is high. Therefore, it is imperative to develop an appropriate biomass estimate to assess the contribution of these ecosystems to climate change regulation. This task of the study aims to develop site specific allometric equations for estimating the AGB of the *Acacia-Commiphora* biome of Ethiopia by destructive harvesting and to validate and evaluate the existing generic models developed by Brown et al. (1989), Chave et al. (2005) and Chave et al. (2014) for pan-tropical forests and the newly developed biomass estimation models using the data collected from *Acacia-Commiphora* biome of Ethiopia.

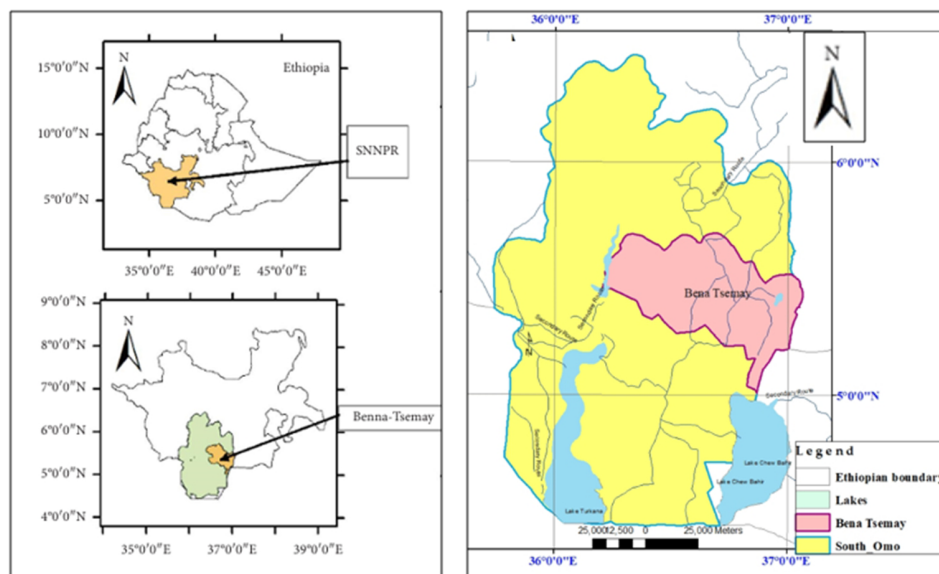
## Materials and Methods

### Site description

*Acacia-Commiphora* biome is found in the northern, eastern, central, and southern parts of Ethiopia and consists of drought-resistant trees and shrubs with evergreen or deciduous leaves, mainly in sandy soils (Friis et al. 2010). Bena-Tsema district is located between 5.11°–5.70° N (Fig. 1) and 36.20°–37.04° E, with average temperatures ranging from 10.1°C to 27.5°C and a mean annual rainfall ranging from 400 to 1,600 mm (Zelege et al. 2021). The study area experiences two distinct periods of rain, known as bimodal rainfall. The first season occurs from mid-March until the end of April and is crucial for crop growth. The second season occurs from mid-October to the beginning of November, and is important for the production of pasture. The study area is 500–2,000 m above sea level (Zelege et al. 2021).

### Sampling design and sample tree selection

The inventory of the trees and shrubs was carried out at and the dominant tree species has been identified; diameter classes and basal area were calculated to determine the relative weight of each diameter class and consequently the number of harvestable trees from each diameter class. An intensive forest inventory was conducted using a stratified random sampling technique and total of 72 sample quadrants with a size of 20 m × 20 m (400 m<sup>2</sup>) were set up along transects at distance of 200 m intervals. In each sample quadrant, all woody species with diameter at breast height (DBH) ≥ 5 cm and total height ≥ 1.5 m were identified and the local names are recorded. Tree density (stems ha<sup>-1</sup>), basal area (m<sup>2</sup> ha<sup>-1</sup>), abundance (number of plots with presence) and importance value index (IVI) were calculated for each species. IVI is the sum of relative density, relative basal area, and relative abundance (Curtis and McIntosh 1950; Kent and Coker 1992; Pascal and Pelissier 1996). The diameter-size structure was formulated with a diameter in-



**Fig. 1** Map of the Bena-Tsemay district showing the location of the study area, south-west Ethiopia.

terval of 10 cm and representative specimen trees in each class are systematically tagged for measuring biomass and biometric variables. This consideration of the diameter size class distribution for the entire population leads to accurate allometric equation development and biomass estimation (Basuki et al. 2009; Roxburgh et al. 2015). The woody species was selected for biomass model development based on the basal area value in the site (Ngomanda et al. 2014; Salis et al. 2006).

### Wood density determination

A sample of 5 cm thick slices (at 1 m and 1.3 m height) was collected from eleven individual trees species felled for the development of biomass models (Dovrat et al. 2019). The fresh weight of each disc sample was taken in the field. Consequently, each disk sample was sealed in a plastic bag and taken to a laboratory in Ethiopian Forestry Development (EFD). The volume of the disc sample was measured by the water displacement method based on Archimedes' principle (Djomo et al. 2010). The displacement weight of the sample was recorded and converted to the fresh volume of the sample using the formula: displacement weight (g)/density of water at standard temperature and pressure. The disc samples were then dried at 105°C. for 72 hours in a well-ventilated oven in the laboratory to constant mass (Williamson and Wiemann 2010). Then the oven dry matter of each disk sample and the mean dry matter for each tree species were determined. The wood base density ( $\text{g cm}^{-3}$ ) of the selected dominant trees was determined by calculating the ratio of the mean oven-dried mass of the disk sample (g) to its respective green volume ( $\text{cm}^{-3}$ ).

### Biomass measurement

The biomass of the 140 individual trees was considered for biomass model development. The branches were delimited and separated into different biomass components:

stem with bark (commercial volume, up to a trunk diameter of 7 cm), large branches (diameter greater than 7 cm), thick branches (diameter between 2 and 7 cm) and thin twigs (diameter less than 2 cm) and foliage. Fresh weights of each component were recorded on site and subsamples are taken from each component and oven dried in the laboratory at 102°C to constant weight. Deciduous biomass aliquots were air dried for 3 days and oven dried at 70°C for 24 hours. The total dry weight of a tree was obtained by summing the dry weight of stem, branches and foliage. Stems and large branches (> 7 cm in diameter) was estimated using the Smalian's formula (Picard et al. 2012) and converted to biomass using wood density.

### Model validation and comparison

Widely used allometric models (Brown 1997; Chave et al. 2005, 2014) as well as regional models (Kuyah et al. 2012; Mokria et al. 2018; Ubuy et al. 2018) were applied to our data set for validation. In addition, the biomass expansion factor and mean wood density were taken from the global database to assess their impact on the biomass estimate. In addition, the developed allometric models were evaluated to measure their strength and accuracy while selecting the best goodness of fit. Also, the model developed in this study was validated on 30% of the total sample trees that were not included in the model development. This evaluation and selection can be done using several statistical parameters (Parresol 1999). The root mean square error (RMSE) was used to measure model bias, precision, or accuracy. The coefficient of determination ( $R^2$ ), the Akaike Information Criterion (AIC) (Chave et al. 2005), and the Schwarz Bayesian Information Criterion (SBC) were used to select the most appropriate models. Therefore, models have the lowest value of RMSE, SBC, AIC, and the higher value of  $R^2$  has been selected.

## Allometric biomass models

Several site-specific allometric equation have been developed based on nonlinear regression model techniques (Basuki et al. 2009; Brown et al. 1989; Chave et al. 2005). Allometric scaling relationships for biological phenomena do not have a linear relationship due to the variability of their dimensions. This heteroscedasticity can be adjusted by transforming the data into logarithmic functions. Then, nonlinear regression, most frequently used, approach was adopted for this study (Table 1).

## Data analysis

Data analyzes were generated using SAS Studio 3.8 (SAS Institute Inc., Cary, NC, USA). All relevant statistical tests including normality, multicollinearity, homoscedasticity, and heteroscedasticity were performed. Therefore, data were converted to logarithmic functions. Finally, multiple regression techniques were used to develop allometric models to predict AGB from independent variables including diameter at breast height (D), diameter at stump height at 10 cm (DSH<sub>10</sub>), diameter at stump height at 30 cm (DSH<sub>30</sub>), tree height (H), crown width (CW), crown height (CH) and wood specific gravity ( $\rho$ ). In almost all cases, these data points were declared as outliers and excluded from further analysis. After eliminating outliers, the equation parameters were recalculated.

## Results

### Relationship between above-ground biomass and predictor variables

Regression results indicated that each plant dendrometric measurement against total aboveground biomass (AGB<sub>Total</sub>) showed strong relationship except CH and  $\rho$ , which had the poorest adj-R<sup>2</sup> of 0.6388 ( $p < 0.001$ ) and 0.0861 ( $p = 0.312$ ), respectively as compared to DSH<sub>10</sub> (adj-R<sup>2</sup> = 0.8548),

**Table 1** General equations used in the aboveground biomass model development

Model code	Model form
M <sub>1</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (D)$ }
M <sub>2</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (\rho \cdot D^2 \cdot H)$ }
M <sub>3</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (D^2 \cdot H)$ }
M <sub>4</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (D) + \beta_2 \text{Ln} (H)$ }
M <sub>5</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (D) + \beta_2 \text{Ln} (CW)$ }
M <sub>6</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (D) + \beta_2 \text{Ln} (H) + \beta_3 \text{Ln} (CW)$ }
M <sub>7</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (\rho \cdot D^2 \cdot H) + \beta_2 \text{Ln} (CW)$ }
M <sub>8</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (\rho \cdot D^2 \cdot H) + \beta_2 \text{Ln} (CW) + \beta_3 \text{Ln} (DSH_{30})$ }
M <sub>9</sub>	AGB <sub>est.</sub> = exp { $\alpha + \beta_1 \text{Ln} (DSH_{30}) + \beta_2 \text{Ln} (\rho) + \beta_3 \text{Ln} (CW)$ }

AGB: aboveground biomass; Exp: exponential function; Ln: natural logarithm; D: diameter at breast height (cm); H: total tree height (m);  $\rho$ : basic wood density (g/cm<sup>3</sup>);  $\alpha$ : constant;  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ : regression parameters.

DSH<sub>30</sub> (adj-R<sup>2</sup> = 0.8582), DBH (adj-R<sup>2</sup> = 0.843), CW (adj-R<sup>2</sup> = 0.7768) and CV (adj-R<sup>2</sup> = 0.90) with  $p < 0.001$  (Fig. 2). The  $\rho$  varies significantly between different species (Ubuy et al. 2018), and is therefore considered important for explaining variations in biomass when developing general biomass models (Chave et al. 2014; Kachamba et al. 2016).

The mean D, DSH<sub>10</sub>, DSH<sub>30</sub>, CW, H, and CH of the sample trees were 12.61 cm, 14.32 cm, 13.6 cm, 4.46 m, 5.39 m, and 3.86 g cm<sup>-3</sup>, respectively. On other hands, the mean total above ground biomass, stem, branch, and foliage biomass of the samples trees were 61.25, 15.53, 35.42, and 11.05 kg tree<sup>-1</sup>, respectively (Table 2). Furthermore, summary statistics for the felled tree species and above-ground biomass utilized in the development of the biomass equations are provided as supplementary information (Table S1).

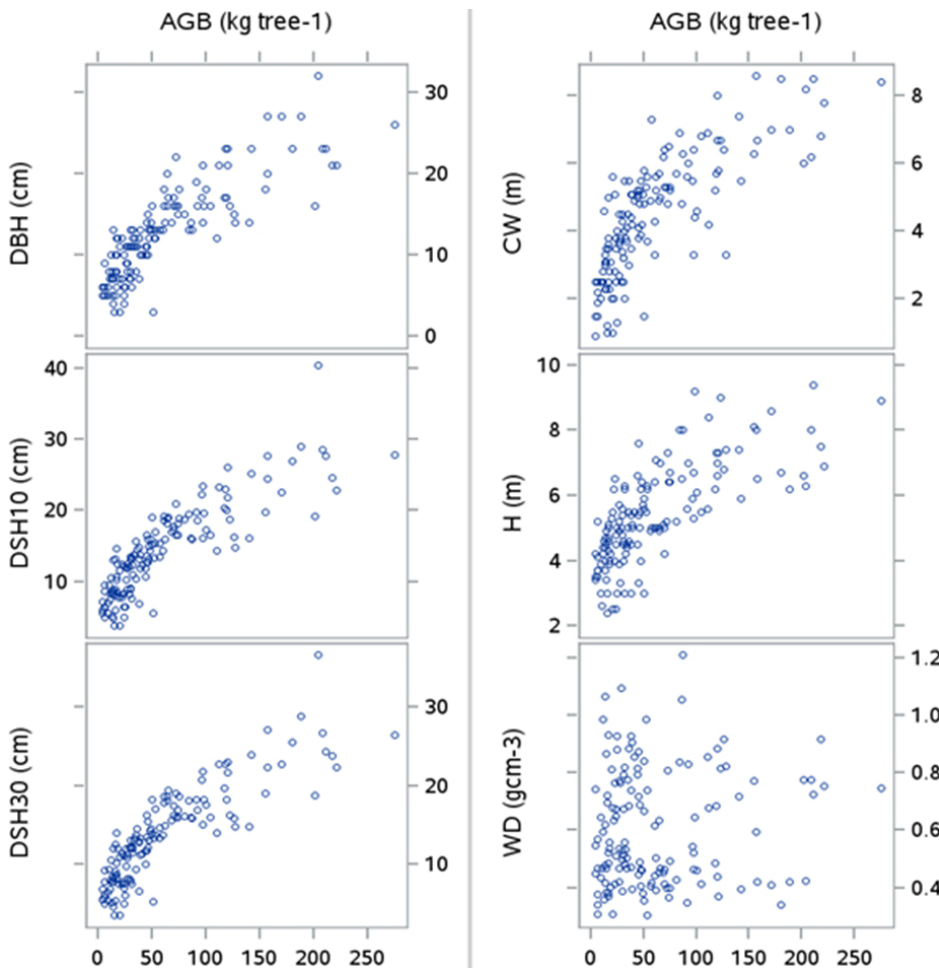
## Allometric models

In this study, we tested nine candidate log-transformed allometric equations (M<sub>1</sub>–M<sub>9</sub>) to develop the best and most accurate allometric models for estimating the foliage, branch, and stem biomass and the AGB<sub>Total</sub> for the eleven tree species. The results of the predictive regression analysis and analysis of variance of the fitted equations and validation statistics are presented in Table 3. The models with high R<sup>2</sup> and adj-R<sup>2</sup> values, low RMSE, AIC and SBC values were used to choose the best-fit models. Therefore, the best performing and accurate allometric models that were found differed among the different species and different components.

Parameter estimates and performance indicators of the total aboveground and section biomass models are presented in Table 3. For the general AGB<sub>Total</sub> models, adj-R<sup>2</sup> ranged from 0.71 to 0.85, and M<sub>9</sub> with DSH<sub>10</sub>,  $\rho$ , and CW as predictor variables, performed best according to RMSE and AIC. For the merchantable stem models, adj-R<sup>2</sup> varied from 0.73 to 0.82, and M<sub>8</sub> with combination of  $\rho$ , DBH, and H, CW and DSH<sub>10</sub> as predictor variables, was best in terms of RMSE and AIC. On other hands, M<sub>8</sub> and M<sub>9</sub> for branch and foliage biomass, respectively, performed best in terms of lowest AIC.

The performance of the branch and foliage biomass models in general appeared to be relatively poor compared to the total aboveground and merchantable stem biomass models. Using DBH as sole predictor explained 67% and 18% of the variations in branch and foliage biomass, respectively. Inclusion of H alone in any form of combinations in the branch and foliage models resulted in insignificant parameter estimates. On the other hand, including CW and DSH<sub>30</sub> as predictor variables improved the model performances.

$$\text{AGB}_{\text{stem}} = \exp \{-1.8296 + 0.4814 \text{ natural logarithm (Ln)} (\rho D^2 H) + 0.1751 \text{ Ln} (CW) + 0.4059 \text{ Ln} (DSH_{30})\}$$



**Fig. 2** Pearson correlation between the tree above ground biomass (AGB) (kg tree<sup>-1</sup>) vs. wood specific gravity (g cm<sup>-3</sup>); diameter at breast height (DBH) (cm); diameter at stump height (DSH) at 10 and 30 cm; crown width (CW) (m); and total tree height (H) (m). WD: wood density.

**Table 2** Summary statistics of the tree variables and above ground tree biomass (n = 140)

	Tree variables						Biomass			
	D	DSH <sub>10</sub>	DSH <sub>30</sub>	CW	H	CH	AGB <sub>Stem</sub>	AGB <sub>Branch</sub>	AGB <sub>Foliage</sub>	AGB <sub>Total</sub>
Mean	12.610	14.320	13.600	4.460	5.390	3.860	15.530	35.420	11.050	61.250
SE	0.489	0.534	0.506	0.151	0.128	0.112	1.332	3.078	0.903	4.694
Range	29.000	36.600	33.200	7.700	7.000	5.800	77.940	188.580	53.670	271.570
CV	45.927	44.182	44.081	40.107	28.146	34.366	101.495	101.722	96.684	90.680

AGB: aboveground biomass (kg tree<sup>-1</sup>); D: diameter at breast height (cm); DSH: diameter at stump height at 10 and 30 cm; CW: crown width (m); H: total tree height (m); CH: crown height (m); SE: standard error; CV: coefficient of variations.

$$AGB_{Branch} = \exp \{-131.6 + 15.0013 \ln (\rho D^2 H) + 13.176 \ln (CW) + 21.8506 \ln (DSH_{30})\}$$

$$AGB_{Foliage} = \exp \{-0.9496 + 0.5282 \ln (DSH_{30}) + 2.3492 \ln (\rho) + 0.4286 \ln (CW)\}$$

$$AGB_{Total} = \exp \{-1.8245 + 1.4358 \ln (DSH_{30}) + 1.9921 \ln (\rho) + 0.6154 \ln (CW)\}$$

The results indicated that the predicted value were strongly correlated with AGB. The best-fit models from all tested models were also tested for accuracy based on observed and predicted data. Observed and predicted above-ground biomass values are close to the 1:1 line (Fig. 3). On other hands, residual plots of the best-fitted equations for our studied species generally indicate an even spread of residu-

als above and below the zero line with systematic trend (Fig. 4). This suggests that natural log-transformed multiple linear regressions are effective in stabilizing error variance, and this study appeared to be appropriate for reducing heteroscedasticity. For total AGB, during statistical analysis, the fit diagnostics and residual by regressors for LnAGB (kg/tree) were displayed below (Figs. 3 and 4).

### Paired comparison for best-fit model and pan tropical models

The logarithmically transformed dataset was subjected to a Shapiro–Wilk and Kolmogorov–Smimov normality test before the paired t-test and showed a normal distribution. The results showed that the new model (M<sub>9</sub>) varied

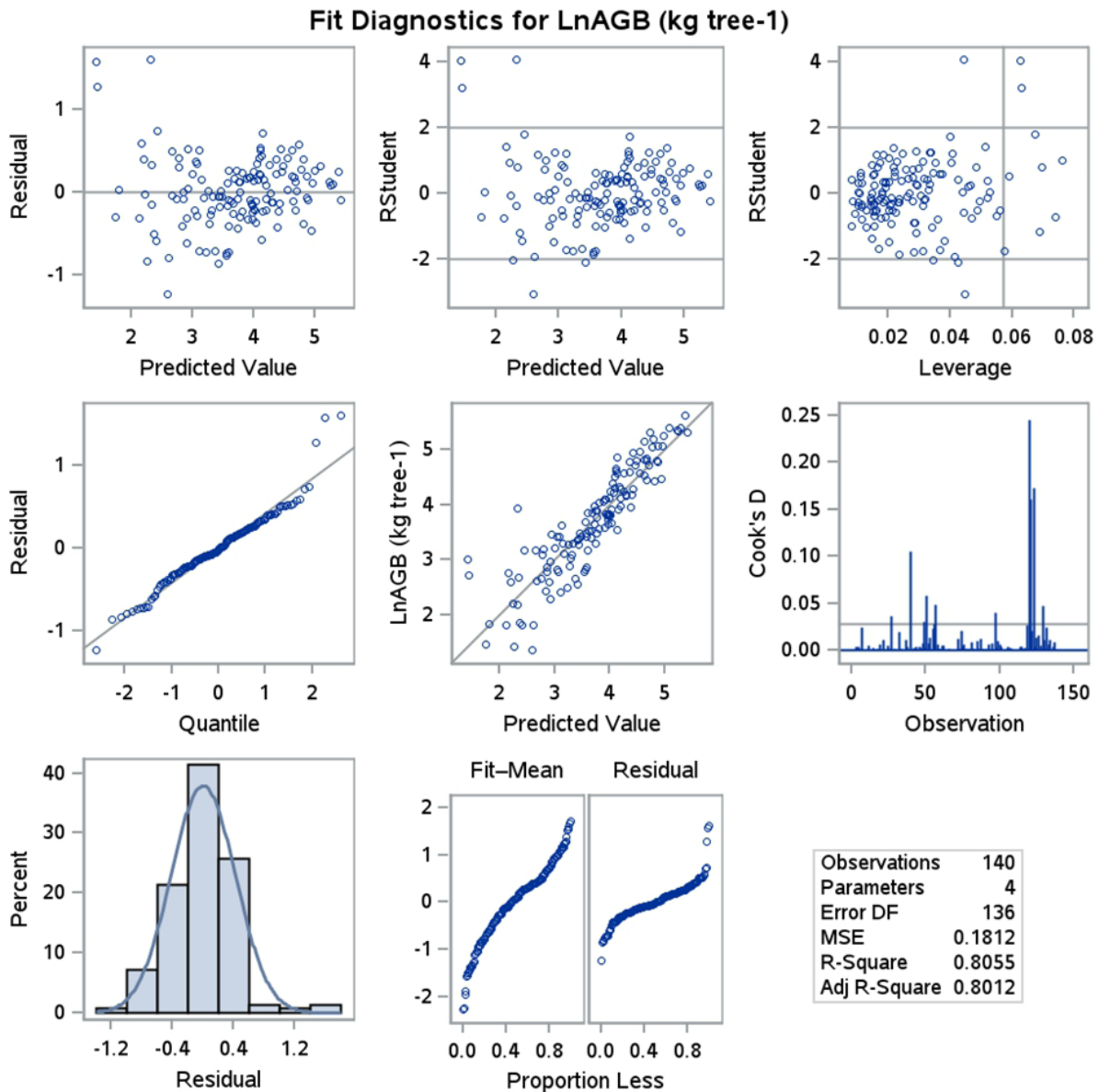
**Table 3** Parameter estimates and model performance statistics of each model for different components of trees (stem, branch, foliage, and total above ground tree biomass) for twelve tree species

Biomass component	Model	Parameter estimates					Model performance statistics							
		$\alpha$	SE	$\beta_1$	SE	$\beta_2$	SE	$\beta_3$	SE	RMSE	R <sup>2</sup>	Adj-R <sup>2</sup>	AIC	SBC
AGB <sub>Stem</sub>	1	-1.3994	0.2264	1.5387	0.0916					0.47	0.73	0.73	-44.04	-131.04
	2	-1.6520	0.1936	0.6715	0.0320					0.39	0.81	0.81	-74.48	-161.48
	3	-2.7620	0.2719	1.0695	0.0565					0.42	0.78	0.78	-61.35	-148.35
	4	-2.0187	0.2430	1.0729	0.1258	1.0633	0.2127			0.42	0.78	0.78	-59.56	-144.06
	5	-1.5288	0.2226	1.1163	0.1574	0.7037	0.2168			0.43	0.77	0.77	-56.86	-141.36
	6	-2.0010	0.2419	0.9225	0.1570	0.3543	0.2235	0.9212	0.2298	0.41	0.79	0.79	-62.78	-144.78
	7 <sup>a</sup>	-1.6919	0.1955	0.6063	0.0591	0.2602	0.1985			0.38 <sup>b</sup>	0.82 <sup>b</sup>	0.82 <sup>b</sup>	-77.29 <sup>b</sup>	-161.79 <sup>b</sup>
	8 <sup>a</sup>	-1.8296	0.2078	0.4814	0.0898	0.1751	0.2022	0.4059	0.2207	0.38 <sup>b</sup>	0.83 <sup>b</sup>	0.82 <sup>b</sup>	-79.27 <sup>b</sup>	-161.27 <sup>b</sup>
	9 <sup>a</sup>	-2.8544	0.2830	1.5033	0.1501	1.6775	0.3246	0.3872	0.1929	0.38 <sup>b</sup>	0.82 <sup>b</sup>	0.82 <sup>b</sup>	-76.85 <sup>b</sup>	-158.85 <sup>b</sup>
AGB <sub>Branch</sub>	1	-114.7558	10.0734	61.3428	4.0425					20.96	0.67	0.67	641.61	554.61
	2	-119.9720	9.4900	25.9467	1.5569					19.52	0.71	0.71	628.86	541.86
	3	-168.8799	12.6504	42.5634	2.6089					19.04	0.73	0.72	624.39	537.39
	4	-136.6919	11.2524	46.9626	5.4368	34.4510	9.1737			19.15	0.73	0.72	626.34	541.84
	5	-121.4085	10.0591	45.8423	6.5831	26.8940	9.1595			19.34	0.72	0.71	628.18	543.68
	6 <sup>a</sup>	-136.7456	11.1713	40.0727	6.7233	16.5493	9.6287	28.1061	9.8273	18.65 <sup>b</sup>	0.74 <sup>b</sup>	0.73 <sup>b</sup>	622.60 <sup>b</sup>	540.60 <sup>b</sup>
	7 <sup>a</sup>	-123.7342	9.5985	21.7083	2.6907	17.5747	9.1444			18.73 <sup>b</sup>	0.74 <sup>b</sup>	0.73 <sup>b</sup>	622.36 <sup>b</sup>	537.86 <sup>b</sup>
	8 <sup>a</sup>	-131.6154	10.1205	15.0013	4.0433	13.1760	9.2358	21.8506	9.9403	18.64 <sup>b</sup>	0.74 <sup>b</sup>	0.74 <sup>b</sup>	622.45 <sup>b</sup>	540.45 <sup>b</sup>
	9	-155.9457	13.4546	54.4668	6.9053	39.9823	14.8594	21.0635	8.9666	19.40	0.72	0.71	629.61	547.61
AGB <sub>Foliage</sub>	1	0.7843	0.3205	0.5706	0.1296					0.75	0.18	0.17	41.57	-45.43
	2 <sup>a</sup>	0.4326	0.3084	0.2926	0.0510					0.71 <sup>b</sup>	0.25 <sup>b</sup>	0.24 <sup>b</sup>	33.07 <sup>b</sup>	-53.93 <sup>b</sup>
	3	0.3152	0.4175	0.3890	0.0867					0.75	0.18	0.17	41.37	-45.64
	4	0.2056	0.4849	0.6048	0.2411	0.2853	0.4180			0.75	0.18	0.16	43.09	-41.41
	5	0.2127	0.4040	0.1638	0.2695	0.9330	0.3600			0.72	0.24	0.22	36.88	-47.62
	6	0.3593	0.4740	0.2083	0.2806	1.0499	0.4110	-0.2755	0.4610	0.73	0.24	0.21	38.50	-43.50
	7 <sup>a</sup>	0.3693	0.3114	0.1893	0.0942	0.4124	0.3163			0.71 <sup>b</sup>	0.27 <sup>b</sup>	0.25 <sup>b</sup>	33.44 <sup>b</sup>	-51.06 <sup>b</sup>
	8	0.0561	0.4176	0.3297	0.1974	0.5111	0.3883	-0.2781	0.4468	0.71	0.27	0.24	35.04	-46.96
	9 <sup>a</sup>	-0.9496	0.4234	0.5282	0.2246	2.3492	0.4857	0.4286	0.2886	0.67 <sup>b</sup>	0.35 <sup>b</sup>	0.33 <sup>b</sup>	24.18 <sup>b</sup>	-57.83 <sup>b</sup>
AGB <sub>Total</sub>	1	-0.1108	0.2361	1.5765	0.0955					0.53	0.71	0.71	-21.56	-108.56
	2	-0.3789	0.2017	0.6896	0.0333					0.44	0.80	0.79	-52.84	-139.84
	3	-1.4200	0.2958	1.0775	0.0614					0.50	0.73	0.73	-29.37	-116.37
	4	-0.5956	0.2632	1.2118	0.1363	0.8325	0.2304			0.50	0.74	0.73	-28.86	-113.36
	5	-0.3013	0.2230	0.9545	0.1577	1.0361	0.2172			0.45	0.79	0.78	-47.56	-132.06
	6	-0.5533	0.2524	0.8511	0.1638	0.8496	0.2331	0.4916	0.2397	0.45	0.79	0.78	-46.28	-128.28
	7 <sup>a</sup>	-0.4699	0.1987	0.5410	0.0601	0.5932	0.2019			0.41 <sup>b</sup>	0.83 <sup>b</sup>	0.82 <sup>b</sup>	-65.60 <sup>b</sup>	-150.11 <sup>b</sup>
	8 <sup>a</sup>	-0.6207	0.2108	0.4041	0.0911	0.4999	0.2052	0.4446	0.2240	0.40 <sup>b</sup>	0.83 <sup>b</sup>	0.83 <sup>b</sup>	-67.43 <sup>b</sup>	-149.43 <sup>b</sup>
	9 <sup>a</sup>	-1.8245	0.2666	1.4358	0.1414	1.9921	0.3057	0.6154	0.1817	0.38 <sup>b</sup>	0.86 <sup>b</sup>	0.85 <sup>b</sup>	-80.68 <sup>b</sup>	-162.68 <sup>b</sup>

$\alpha$ : constant;  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ : fitted parameters; SE: standard error; RMSE: root mean square error; R<sup>2</sup>: coefficient of determination; AIC: Akaike information criterion; SBC: Schwarz Bayesian information Criterion; AGB: aboveground biomass.

<sup>a</sup>The best-fit models.

<sup>b</sup>The statistical values pivotal for the selection of the relevant regression model, which is more suitable for biomass prediction.



**Fig. 3** Fit diagnostics for natural logarithm aboveground biomass (LnAGB) (kg/tree). DF: degree of freedom; MSE: mean square error.

significantly compared to previously developed models (Table 4) (Brown et al. 1989; Chave et al. 2005, 2014; Mokria et al. 2018).

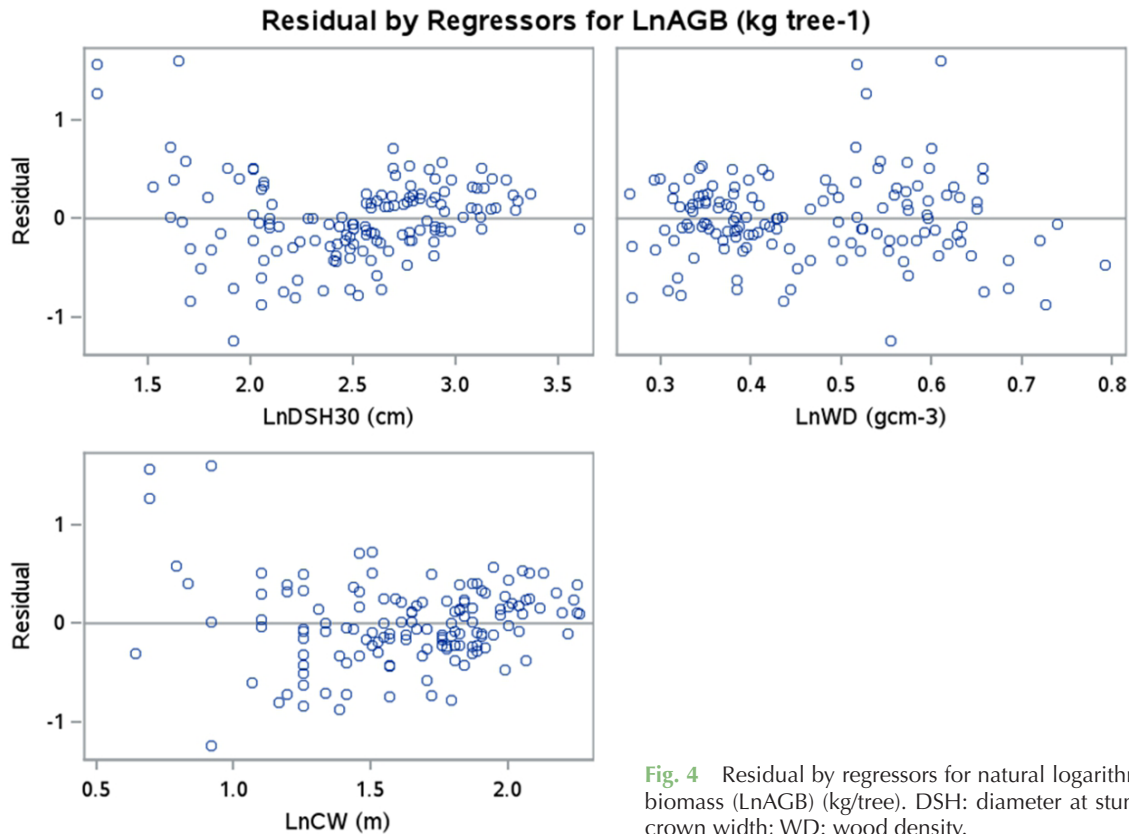
## Discussion

In the present study, we compared the AGB values obtained by the harvesting method with those estimated using the most appropriate general model ( $M_9$ ,  $M_8$ , and  $M_7$ ), pantropical models and regional models (Table 5). We found that the best-fitting general model ( $M_9$ ,  $M_8$ , and  $M_7$ ) was able to accurately predict the biomass with the least variation. However, widely used allometric models (Brown et al. 1989; Chave et al. 2005, 2014) and regional models (Kuyah et al. 2012; Mokria et al. 2018; Ubuy et al. 2018) could not correctly predict AGB for individuals of small

diameter. Furthermore, the most appropriate general model of the present study ( $M_9$ ,  $M_8$ , and  $M_7$ ) showed the lowest RMSE (0.410, 0.404, and 0.375, respectively) compared to the commonly used pantropical models (Brown et al. 1989; Chave et al. 2005, 2014) and regional models (Table 5) (Kuyah et al. 2012; Mokria et al. 2018; Ubuy et al. 2018). The previously developed models were also applied to our dataset and evaluated using RMSE in Table 5.

The widely used regional allometric models (Mokria et al. 2018; Ubuy et al. 2018) overestimated the dry AGB while allometric models (Brown et al. 1989; Chave et al. 2005, 2014) underestimated the dry AGB compared to best-fit models in this study (Fig. 5). Figure 5 graphically shows some of the previously developed models and the  $AGB_{Total}$  ( $M_9$ ,  $M_8$  and  $M_7$ ) model from the current study.

Estimating tree biomass using regional or pantropical allometric biomass models is still common (Chave et al.



**Fig. 4** Residual by regressors for natural logarithm aboveground biomass (LnAGB) (kg/tree). DSH: diameter at stump height; CW: crown width; WD: wood density.

**Table 4** Paired sample t-test for the new ( $M_9$ ) and previously developed models ( $n = 140$ )

Model references	Mean (SE)	DF	Paired t-test	
			t-statistics	p-value
Pair 1 $M_9$ - Brown et al. 1989	1.0099 (0.0337)	139	29.96	< 0.0001
Pair 2 $M_9$ - Chave et al. 2005	1.3205 (0.0313)	139	42.23	< 0.0001
Pair 3 $M_9$ - Chave et al. 2014	1.7699 (0.0313)	139	56.60	< 0.0001
Pair 4 $M_9$ - Mekua et al. 2018	0.0509 (0.0208)	139	2.44	0.0158

$M_9$ : new model 9; SE: standard error; DF: degree of freedom.

**Table 5** Evaluation results of previously developed models when applied on our dataset ( $n = 140$ )

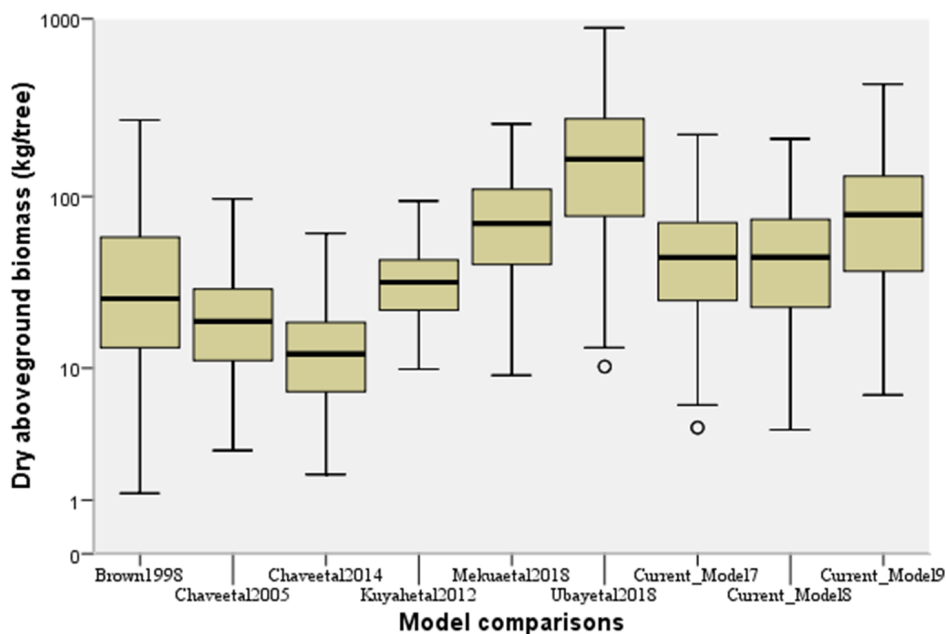
Source	Model	Predicted $AGB_{Total}$	RMSE
Chave et al. (2005)	$AGB_{est.} = 0.112 \times (\rho D^2 H)^{0.916}$	24.5480	4.674
Chave et al. (2014)	$AGB_{est.} = 0.0673 \times (\rho D^2 H)^{0.976}$	15.6628	2.982
Kuyah et al. (2012)	$AGB_{est.} = 0.225 \times D^{2.341} \times H^{0.73}$	35.5674	4.854
Mokria et al. (2018)	$AGB_{est.} = 0.2451 \times (DSH^2) \times H^{0.7038}$	83.1133	9.685
Ubuy et al. (2018)	$AGB_{est.} = 0.3102 \times (DSH)^{1.5155} \times (CW)^{0.6453}$	196.1653	33.704
Brown et al. (1989)	$AGB_{est.} = \exp \{-2.4090 + 0.9522 \times \ln(\rho D^2 H)\}$	44.5441	0.994
Current study $AGB_{Total}$ ( $M_7$ )	$AGB_{est.} = \exp [-0.4699 + \{0.5410 \times \ln(\rho D^2 H)\} + \{0.5932 \times \ln(CW)\}]$	55.4203	0.410
Current study $AGB_{Total}$ ( $M_8$ )	$AGB_{est.} = \exp [-0.6207 + \{0.4041 \times \ln(\rho D^2 H)\} + \{0.4999 \times \ln(CW)\} + \{0.4446 \times \ln(DSH_{30})\}]$	55.4959	0.404
Current study $AGB_{Total}$ ( $M_9$ )	$AGB_{est.} = \exp [-1.8245 + \{1.4358 \times \ln(DSH_{30})\} + \{0.9921 \times \ln(\rho)\} + \{0.6154 \times \ln(CW)\}]$	95.5803	0.375

Observed mean  $AGB_{Total} = 61.2557$  kg.

AGB: aboveground biomass; RMSE: root mean square error;  $\rho$ : wood specific gravity ( $g\ cm^{-3}$ ); volume:  $m^3$ ; D: diameter at breast height (cm); H: total tree height (m); DSH: diameter at stump height at 30 cm; CW: crown width (m); Ln: natural logarithm.

2014). However, using these models for biomass estimation shows large differences in biomass estimates compared to species-specific allometric equations (Ngomanda et al.

2014). The best-fitting general model showed less variation in  $AGB_{Total}$  estimates compared to the commonly used pan-tropical and regional models. Similar results have been re-



**Fig. 5** Model comparison to previously developed and current best-fit models.

ported in previous studies (Kenzo et al. 2009; Pothong et al. 2022). This may be because these pantropical biomass models were developed using data from individuals at larger diameters and from different geographic locations. This could be supported by the results of Fonseca et al. (2012) who found that the error in biomass estimation can also occur when the equations are applied to diameter ranges outside of that used for their formulation. In addition, models that focus on larger trees may overestimate the biomass of smaller trees (van Breugel et al. 2011).

## Conclusions

The use of pantropical and regional models should therefore be questioned in terms of the sample source used to develop the model against local forest variation before they are widely applied. The first general aboveground tree biomass models for the *Acacia-commiphora* biome in southern Ethiopia have been developed. The models were developed from a large dataset with 140 sampled individual trees and 11 woody species. The statistical results of the selected models were satisfactory and the evaluations revealed no serious shortcomings. The generally large prediction errors observed when testing the “pan-tropical” models and previously developed local models on our data demonstrated the importance of developing new models. The results of this study show that the development of local models derived from an appropriate sample of representative species can significantly improve the estimation of the overall AGB. In conclusion, the best-fit models presented in this study can provide more confidence in estimating the biomass in the study area. The models may be used for decision support as a basis for reporting on chang-

es in biomass and carbon stock according to REDD<sup>+</sup> mechanism requirements.

## Supplementary Information

Supplementary information accompanies this paper at <https://doi.org/10.5141/jee.24.036>.

**Table S1.** Summary statistics of the felled tree species and above ground biomass used to develop the biomass equations in the study.

### Abbreviations

CRGE: Climate Resilient Green Economy

GHG: Greenhouse gas

MRV: Measurement, reporting, and verification

AGB: Aboveground biomass

DBH: Diameter at breast height

IVI: Importance value index

EFD: ETHIOPIAN Forestry Development

RMSE: Root mean square error

AIC: Akaike Information Criterion

SBC: Schwarz Bayesian Information Criterion

DSH: Diameter at stump height

D: Breast height

H: Tree height

CW: Crown width

CH: Crown height

$\rho$ : Wood specific gravity

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### Authors' contributions

WA performed statistical analysis and prepared the manuscript, WA, CT, and DG designed methodology and collected field data. ZM conceived the study, designed the research framework, and provided supervision throughout the study. All authors read and approved the final manuscript.

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### Availability of data and materials

The data sets are available from the corresponding author upon reasonable request.

### Ethics approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Competing interests

The authors declare that they have no competing interests.

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