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Volume and aboveground biomass models for a dry evergreen montane forest in Tanzania

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Abstract. *Mwaluseke ML, Mwakalukwa EE, Maliondo SMS. 2023. Volume and aboveground biomass models for a dry evergreen montane forest in Tanzania. Asian J For 7: 45-53*. Models available for accurately estimating trees and shrubs' volume and aboveground biomass from dry evergreen montane forests in Tanzania are largely lacking. Therefore, this study was conducted to develop volume, and aboveground biomass models for a dry evergreen montane forest of Lendikinya Forest Reserve found in Northern Tanzania. A total of thirty sample trees and shrubs with a diameter range of 5-58.5 cm were destructively harvested and used in this study. Specifically, the study developed (i) the height-diameter model and (ii) the total volume and aboveground biomass models. The following height, volume, and biomass models appear to be suitable for estimating tree height, volume, and biomass of tree and shrub species found in the study site: Height (m) =2.3249 + 6.6101/DBH + 0.2847DBH (R2 = 0.78, RMSE = 1.79, AIC = 164.37), ln(Volume, m^3) = -9.845 + 1.915 ln(DBH) + 1.089ln(Ht) (R2 = 0.97, RMSE = 0.296, AIC = -144.18) and ln(Biomass, kg) = -1.666 + 0.853ln(WD x DBH2 x Ht) (R2 = 0.95, RMSE = 0.324, AIC = 224.13). Both models yielded low bias, hence indicating an excellent fit. These models will be useful in understanding the condition of the forest and the potential of this forest in storing carbon hence, the possibility of benefiting from the ongoing negotiations of REDD+ schemes for payment for avoided deforestation and degradation through sustainable management of the reserve.

Keywords: Allometric, biomass, carbon, evergreen, Lendikinya Forest Reserve, models

INTRODUCTION

There is increasing interest in understanding the contribution of forest ecosystems in mitigating climate change effect (Lorenz and Lal 2010; Njana et al. 2018; Mauya et al. 2019; Leley et al. 2022; Mauya et al. 2022; Nugroho et al. 2022). That can be achieved by quantifying the carbon currently locked up in these ecosystems (Njana et al. 2018; Mauya et al. 2019; Leley et al. 2022). The estimation or quantification of carbon stocks is based on allometric equations developed in the same forests or similar vegetation types in cases where there are no existing models for such a specific forest (Chave et al. 2005; Henry et al. 2011; Ngomanda et al. 2014; Mwakalukwa et al. 2014). However, it is generally accepted that indirect methods using allometric volume equations, form factor and biomass expansion factors and/or with basic wood density (Chave et al. 2014; Njana et al. 2017) and models developed from other vegetation types to some extent, do not provide reliable estimates of carbon stocks in the studied vegetation (Henry et al. 2011; Chave et al. 2014; Djomo et al. 2016; Njana et al. 2018; Mauya et al. 2019). Specific models for each vegetation type are more precise in estimating biomass hence carbon stocks of the particular forest compared to the generalized models developed from other or similar vegetation types (Brown 2002; Mugasha et al. 2013; Chave et al. 2014; Daba and Soromessa 2019; Mauya et al. 2019; Asrat et al. 2020). Therefore, it is encouraged that locally specific models be developed to improve the accuracy and predictive capacity of the models using samples obtained from the same vegetation types (Mugasha et al. 2013; Mauya et al. 2014; Mwakalukwa et al. 2014; Feyisa et al. 2018; Njana et al. 2018; Asrat et al. 2020). That is especially very important when the country (project) is expecting to benefit from the ongoing initiative of payment for Reducing Emission from Deforestation and Degradation (REDD+) (Njana et al. 2018; Mauya et al. 2019; Mauya et al. 2022).

According to Mauya et al. (2019), countries are required to develop four key components if they aim to undertake REDD+ activities and to be eligible for financial compensation (FAO 2014): (i) a national strategy or action plan; (ii) a national forest reference emission level (FREL) and/or forest reference level (FRL); (iii) a robust and transparent national forest monitoring system for Measurement, Reporting and Verification (MRV) of the REDD+ activities; and (iv) a system for providing information on how the safeguards are addressed or respected. The Tanzania mainland has up-to-date national forest inventory data collected through a National Forest Resources Monitoring and Assessment (NAFORMA) Project between 2009 and 2014 (MNRT 2015). Those data could serve to address the above requirements. In addition, the availability of as many up to date allometric models to assist in quantifying existing carbon stocks and estimating potential emissions is necessary.

In Tanzania, most of these models have been developed for different vegetation types (Malimbwi et al. 2016). Specifically, models have been developed for Miombo forests (Mugasha et al. 2013; Mauya et al. 2014; Mwakalukwa et al. 2014; Manyanda et al. 2019), mangrove forests (Njana et al. 2016a,b), lowland forests (Mugasha et al. 2016a), mountain humid/rain forest (Masota et al. 2014; Masota et al. 2015), thicket and associated trees (Makero et al. 2016), *Acacia-Commiphora* woodlands (Mugasha et al. 2016b) and plantation forests (Mugasha et al. 2016c; Zahabu et al. 2016). However, no volume and biomass models have been developed for dry evergreen montane forests in Tanzania, unlike other areas such as Ethiopia that have been studied (Tetemke et al. 2019; Asrat et al. 2020).

This study intended to provide robust stand volume and biomass models for dry evergreen montane forests of Lendikinya Forest Reserve (LFR) in Northern Tanzania to assist in better planning and management. Stand-level models can also help to understand the contribution of the forest in mitigating climate change based on future REDD+ initiatives in Tanzania, particularly for effective monitoring, reporting, and verification of Greenhouse Gas (GHG) emissions. Therefore, the specific objective of the study was to develop volume and aboveground biomass models of trees and shrubs with a diameter ≥ 5 cm found in the LFR. The models would be used for dry evergreen montane forests in that region.

MATERIALS AND METHODS

Study area description

Lendikinya Forest Reserve (LFR), with a total area of 3,689 ha and gazetted in 1969 (JB No. 1854), is a dry evergreen montane forest located in the eastern part of Monduli District (latitudes 2° and 4° S and longitude 36° and 37° E) in Arusha Region, Tanzania (Meindertsma and Kessler 1997) (Figure 1). Monduli Local Government Authority manages the LFR. Generally, the district's climate is arid to semi-arid, with average rainfall between 400 to 900 mm per annum and wide variations in relief and soil types (UNDP 2003). The weather range from as low as 11.5°C in July to a maximum temperature of up to 29°C in December. For the lower altitudes in May, humidity during the night reaches 100%. LFR is surrounded by four villages: Lashaine, Monduli Juu, Alkatani, and Lendikinya. Moreover, the economic activities of the people of the area depend on livestock, agro-pastoralism, and tourism. LFR forms part of the rift valley characterized by depressions. The woodland harbors large wild animal species such as *Loxodonta africana* (Elephants), *Giraffa camelopardalis* (Giraffe), *Syncerus caffer* (Buffaloes), and a variety of birds and insects (Meindertsma and Kessler 1997; UNDP 2003).

Field sampling

The field survey was conducted in May-June 2014. A total of 30 sample trees and shrubs (Table 1) with a diameter range of 5-58.5 cm were selected based on species composition and diameter classes of species available in the forest (Mwaluseke 2015, unpublished data). The selection ratio was five trees to 1 shrub (Chaturvedi and Raghubanshi 2012; Mwakalukwa et al. 2014; Malimbwi et al. 2016; Asrat et al. 2020; Teshome et al. 2022). Few shrubs were selected because they possessed lower diameter size classes and are the least contributor to total volume and biomass than the large-sized trees (Asrat et al. 2020; Teshome et al. 2022). The selected trees and shrubs species were first identified before they were felled (Table 2) (Mwakalukwa et al. 2014; Malimbwi et al. 2016). After identification, the trees were measured for diameter at breast height (DBH at 1.3 m) using diameter tape/caliper to the nearest 0.1 cm (Teshome et al. 2022). The trees were also measured for their height using a Suunto hypsometer. In addition, height measurements were also taken for the three selected stems (small, medium, and largest in terms of diameter) using the same instrument (a Suunto hypsometer). Next, the tree was felled 10 cm from the ground level using a chainsaw. Then, using a tape measure, the total height of the felled tree was measured before it was segregated into different components: stems, branches, and leaves (Mugasha et al. 2013; 16a). The upper diameter limit selection depends on the wood's utilization (Mwakalukwa et al. 2014). In the study area, the important use of the wood was mainly for poles and timber production, with few tree species used for charcoal production, mainly utilizing the top diameter of the 5 cm portion. Therefore, both volume and biomass models were developed based on DBH ≥ 5 cm.

For each felled sample tree, twigs and leaves were removed from branches and tied into bundles (piles) (Mandal et al. 2013; Mwakalukwa et al. 2014; Mugasha et al. 2016a; Asrat et al. 2020). Depending on their weights, stem and branch billets were tied in bundles and weighed separately to obtain green weights, and eventually, the green weight of a whole tree was obtained by summating the weight of individual tree sections (Mwakalukwa et al. 2014; Mugasha et al. 2016a). The subsamples were then weighed using a Portable Digital scale, while large and heavy billets or piles were weighed using a conventional scale (Asrat et al. 2020). For dry weight estimation, a subsample from each pile of twigs and leaves and two stem discs (one from the stem at 1.3 cm aboveground and one from a branch at approximately 30 cm from the point of branching) were obtained and weighed for green weight in the field and taken to the laboratory for oven-dry weight determination (Mandal et al. 2013; Asrat et al. 2020). All samples were carefully marked for respective species names, tree numbers, and DBH. The lightweight data was packed in envelopes for laboratory analysis. Furthermore, to facilitate biomass weighing and the construction of volume models, each of the stem and branch sections of the felled trees was trimmed into billets of length 1-2.5 m and measured at mid-diameters (dm) (Malimbwi et al. 1994; Mugasha et al. 2013; Asrat et al. 2020).

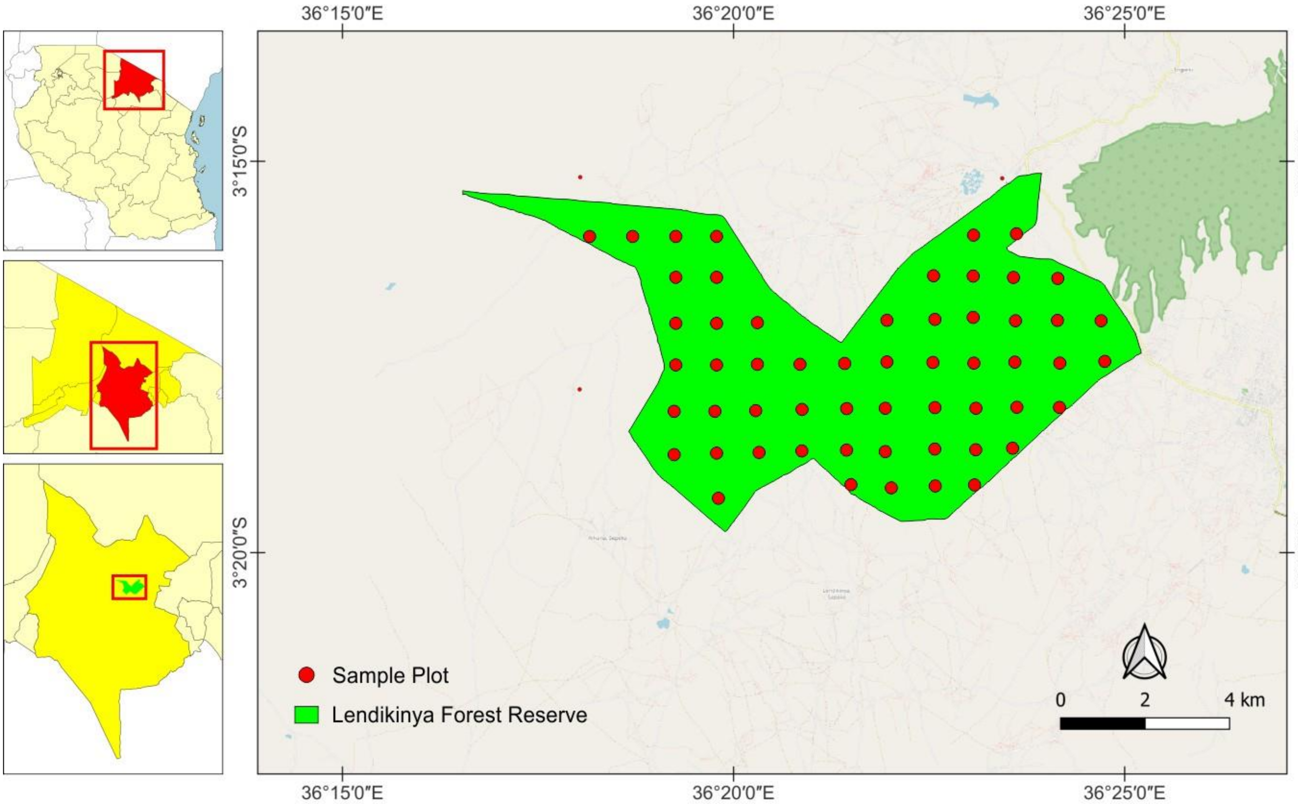

Figure 1. Location of Lendikinya Forest Reserve in Monduli District, Arusha, Tanzania

Laboratory analyses

In the laboratory, all large disc samples were split into small blocks and marked. Then, all block subsamples were soaked in water for seven days until they were saturated (Malimbwi et al. 1994; Mugasha et al. 2013). After that, the water displacement method was used to determine the green volume of each subsample (i.e., small discs and blocks) (Chaturvedi and Raghubanshi 2012). Eventually, the subsamples were oven-dried at a standard temperature of 103 ± 2°C for four and half days to a constant weight, and their oven-dry weight was recorded (Mandal et al. 2013; Mwakalukwa et al. 2014; Asrat et al. 2020). Wood basic density (g cm^{-3}) was determined as the ratio of oven-dry weight to fresh volume, while dry biomass was computed by multiplying the fresh weight with oven-dry weight to green weight ratio (Chaturvedi and Raghubanshi 2012; Mwakalukwa et al. 2014; Njana et al. 2016a,b; Asrat et al. 2020).

Data preparation

Before the model development, data were assessed for additivity (Mugasha et al. 2016a). The additivity concept was attained by summing the biomass and volume components (stem wood, branches, and leaves). Thus, ensuring that the total biomass and volume obtained equaled the total biomass and volume predicted by allometric equations (Asrat et al. 2020; Teshome et al. 2022). Next, for each tree, the volume of individual stems and branch billets was calculated using Huber's formula ($V=\pi\ Ld^2_m/4$; where d_m= Billet's mid-diameter, L=Billet length, π = Pai, V= billet volume). Then, the total volume of each sample tree/shrub with a diameter ≥ 5 cm was calculated by adding the individual volume of stem and branch billet sections. This dataset was used to develop mixed-species volume models (Mwakalukwa et al. 2014; Mauya et al. 2014).

Dry biomass (kg) was estimated as the product of estimated biomass ratios (oven-dry to fresh weights) for each subsample (i.e., stem and branch discs and leaves) and their corresponding fresh weights (kg) measured in the field. The total aboveground biomass of each tree was the sum of individual oven-dry biomass of stem, branch, and leaves (Mugasha et al. 2013; Mugasha et al. 2016a; Asrat et al. 2020). The resulting dataset was used to develop aboveground mixed-species-biomass models.

Statistical analysis

Before volume and biomass models were developed, height models were developed to determine the heights of unmeasured live trees and shrubs (Mwakalukwa et al. 2014; Mugasha et al. 2016a). A total of 139 of both felled and unfelled sample trees and shrubs were mixed to capture their variations and accuracy in the estimates. The height dataset was then fitted to the formulated models, as shown in Table 3. DBH was the only predictor variable in the height models, while height (H) was the dependent variable.

For the volume and biomass models development, logarithmic linear models formulated and used elsewhere (Malimbwi et al. 1994; Mwakalukwa et al. 2014) in other forests for the prediction of either volume or biomass or both were also adopted in this study (Table 4). In these models, both dependent and independent (i.e., DBH and height) variables were natural logarithmic transformed to attain linearity. The transformation was also intended to reduce he heteroscedasticity's effect and obtain models that fit the dataset well.

Model 5 in (Table 4) partly resembled model 2, but model 5 further included average wood basic density, intended to capture its contribution to biomass prediction by the model (Chaturvedi and Raghubanshi 2012; Njana et al. 2016a,b). In transformed regression equations, the analysis of the models was preceded by plotting dependent variables (volume and biomass) against each of the independent variables (DBH and height) to determine the range and likely shape of the functional relationship and the heteroscedasticity assessment (Mwakalukwa et al. 2014). Since logarithmic transformation leads to another problem of geometric mean instead of arithmetic mean in the predicted output, a correction factor "CF" following Baskerville (1972) was used. Those equations ((CF = exp(MSE/2) where MSE = Mean Square Error of the regression, CF = A Correction Factor, Exp = Exponential function)) were used to solve the problem by multiplying it with the predicted output after back-transformed.

The statistical tests employed in evaluating the models regarding the goodness of fit criteria follow Parresol (1999) and Mandal et al. (2013). According to FAO (2012), the most frequently used statistical tests in determining the performance of a model were: coefficient of determination (R^2), Root Mean Square Error (RMSE), and Akaike's Information Criterion (AIC), all of which were computed by the following equations (R^2 = 1-RSS/TSS, where; R^2 = coefficient of determination, RSS = Residual sum of squares, TSS = Total Sum of Squares; RMSE = √RSS/n-Ψ, Where; n = Number of observations in a data model, (Ψ) = Number of parameters present in a model, RSS = Residual sum of squares, RMSE = Root Mean Square Error, and AIC = n(lnRSS/n)+2k, Where; n = Number of data points (observations) in a given equation, ln = Natural logarithm, RSS = Residual Sum of Squares, k = Number of parameters in a given equation, AIC = Akaike's Information Criterion) respectively. For each category available, the best model selected had higher R^2 but lower RMSE and AIC values (Parresol 1999; Mugasha et al. 2013; Asrat et al. 2020).

Table 1. Distribution of felled sample trees

Diameter class (cm)	5-10	10.1-20	20.1-30	30.1-40	40.1-50	> 50
Number felled	3	10	8	4	2	3

Table 2. Felled sample trees showing their DBH, height, basic density, volume, and biomass content

Botanical Name	Dbh (cm)	Height (m)	Stem (ρ) (gcm^{-3})	Branch(ρ) (gcm^{-3})	Volume (m^3)	Biomass (kg)
Euclea natalensis A.DC.	5.0	6.2	0.614	0.583	0.0158	13.0283
Turraea holstii Gürke	7.5	4.5	0.509	0.448	0.0055	11.2261
Capparis tomentosa Lam.	10.0	4.6	0.735	0.733	0.0273	32.224
Clausena anisata Willd. Hook. f. ex Benth	10.9	8.0	0.704	0.559	0.0383	30.9263
Indigofera sp.	12.3	7.3	0.506	0.481	0.0527	37.7481
Vangueria madagascariensis J.F.Gmel.	13.8	6.3	0.514	0.528	0.0541	39.5458
Carissa edulis (Forssk.) Vahl	15.0	9.6	0.680	0.606	0.0927	130.867
Elaeodendron buchananii (Loes.) Loes	16.1	5.0	0.624	0.603	0.0722	46.3013
Hibiscus sp.	17.0	4.7	0.612	0.600	0.0793	94.080
Ozoroa insignis Delile	18.5	8.4	0.510	0.426	0.1679	105.683
Teclea simplicifolia (Engl.) I. Verd	19.0	7.7	0.749	0.685	0.1611	175.140
Albizia schimperiana Oliv.	19.9	15.6	0.487	0.512	0.2699	156.608
Vangueria madagascariensis J.F.Gmel.	20.0	3.8	0.521	0.508	0.0577	26.570
Ozoroa insignis Delile subsp. latifolia	20.5	11.9	0.529	0.531	0.5090	246.516
Calodendrum capense (L.f.) Thunb.	20.6	15.0	0.484	0.440	0.3553	196.553
Acacia xanthophloea Hochst. Ex Benth.	21.0	11.7	0.740	0.671	0.2438	255.754
Celtis africana Burm.f.	22.0	14.8	0.562	0.643	0.2824	206.441
Olea sp.	24.0	9.5	0.707	0.703	0.2748	328.615
Maytenus senegalensis (Lam.) Exell	26.0	6.5	0.685	0.640	0.2579	159.633
Maytenus senegalensis (Lam.) Exell	27.4	7.8	0.673	0.608	0.2815	173.052
Acacia nilotica (L.) Willd. ex Delile	28.4	11.2	0.797	0.735	0.4143	358.659
Calodendrum capense (L.f.) Thunb.	30.1	10.0	0.583	0.480	0.4537	273.221
Acacia xanthophloea Hochst. Ex Benth.	32.3	12.8	0.766	0.654	0.7446	514.147
Acacia nilotica (L.) Willd. Ex Delile	33.1	11.3	0.746	0.708	0.6321	400.086
Albizia schimperiana Oliv.	38.7	16.2	0.485	0.490	0.8717	497.065
Celtis africana Burm.f.	41.0	18.8	0.667	0.662	1.1654	671.814
Acacia gerradii Benth.	43.0	14.6	0.816	0.786	1.2700	770.793
Diospyros abyssinica subsp. abyssinica	50.1	21.3	0.628	0.644	2.5103	1339.99
Vangueria madagascariensis J.F.Gmel.	54.0	20.6	0.561	0.473	3.8998	1748.28
Vangueria madagascariensis J.F.Gmel.	58.5	23.8	0.552	0.539	4.4837	2062.34

Table 3. Height model forms tested

Model No.	Height model form
1	$H = b_0 + b_1DBH$
2	$H = 1.3 + b_1DBH + b_2DBH^2$
3	$H = b_0 + \frac{b_1}{DBH} + b_2DBH$
4	$H = \left(\frac{b_0DBH}{b_1 + DBH}\right) - b_2$

Note: H=Tree height, b_o,= Intercept of DBH, b_1, and b_2 are constant parameters while DBH is as defined previously

Table 4. Volume and biomass model forms tested

Model No.	Model form
1	$Ln\ (Y) = a + b \times Ln\ (DBH) + c \times Ln\ (DBH^2) + d \times Ln\ (Ht) + e \times Ln(Ht^2)$
2	$Ln\ (Y) = a + b \times Ln\ (DBH^2 \times Ht)$
3	$Ln\ (Y) = a + b \times Ln\ (DBH) + c \times Ln\ (Ht)$
4	$Ln\ (Y) = a + b \times Ln\ (DBH)$
5	$Ln\ (Y) = a + b \times Ln\ (WD \times DBH^2 \times Ht)$

Note: Y=Volume (m^3) or Biomass (kg); DBH (cm) and Ht=Tree height (m) and a, b, c, d, and e are constant parameters to be analyzed, Ln = natural logarithm, WD = Wood basic density

The accuracy of the model was checked by percentage bias (PBIAS = $\sum(X_{obs}-X_{pre})/\sum X_{obs})x100$, where; PBIAS = Percentage Bias, X_{obs} = Observed value derived from the equation, X_{pre} = Predicted value derived from the equation). According to Mandal et al. (2013), the Percentage Bias (PBIAS) was used to compare and evaluate the predicted and observed values for accuracy assessment. The lowest value of PBIAS indicated by a candidate model gives a better-fit result (Mandal et al. 2013). Regarding Osman et al. (2013), a graphical plot on residuals versus predicted values was important in visualizing the performance of prediction models. The best-selected models were then used to predict corresponding height, volume, and dry biomass quantities (Mugasha et al. 2013; Mwakalukwa et al. 2014; Asrat et al. 2020). All analyses were carried out in Microsoft Excel Spreadsheet, PAST, and Minitab 15 software.

RESULTS AND DISCUSSION

Height models

Four model forms were formulated to predict height as a dependent variable, with diameter as the independent variable (Table 5). First, model 2 had the lowest R^2 value but the highest values of RMSE and AIC. That indicates the poorest performance of all other models. Next, models 1, 2, and 4 had similar RMSE values (1.79). Then Models 1 and 4 had similar R^2 values (0.77). Finally, Model 3 had the highest R^2 and the lowest AIC value of all other models. The goodness of fit shown by model 3 implied that the model fitted the data well and was considered the best model for the height prediction for the unmeasured tree heights.

When standardized residuals for model 3 were plotted against predicted values, it showed that most of the residuals were evenly distributed on both sides but were mostly closer to the horizontal line (zero), indicating the model fitted the data well (Figure 2). In addition, the model also had a very small bias of 0.23%, indicating a reduced error in the height prediction.

Volume models

Four models were parameterized for volume prediction. Table 6 shows that all four models had higher R^2 values ranging from 0.91 to 0.97. Model 1 had higher R^2 and AIC values than all other models except for parameter "a." All other parameters were insignificant at $p < 0.05$, indicating poor performance than other models. Like model 1, model 2 had higher $R^{2,}$ but all other parameters were significant at $p < 0.05$, and their AIC value was much lower than model 1, indicating it is a better model. Model 3 had a similar R^2 value as models 1 and 2 but was not comparable with model 4, which had the lowest R^2 and highest RMSE and PBIAS indicating poor performance than all other models. Since model 3 had the lowest AIC and percentage bias, it was considered the best model for volume prediction.

When standardized residuals of model 3 were plotted against predicted values (Figure 3), the scatter plot did not show any noticeable pattern. Most standardized residuals were distributed close but along the horizontal line (zero), implying that a model fitted well the data.

Biomass models

Five model forms were parameterized for biomass prediction (Table 7). Results showed high values of R^2 with a range of 0.89 to 0.96. Since model 1 had the highest R^2 and smallest values of RMSE and AIC, it was expected to be the best model, but almost all its parameters were not significant at ($p < 0.05$). Apart from models 1 and 4, all other models had equal R^2, but higher values of RMSE and AIC and all their parameters were significant at ($p < 0.05$). Among the significant models, that is, models 2 up to 5, it was observed that model 5 had the lowest RMSE and AIC values than the other three significant models indicating it to be the best model.

When standardized residuals for model 5 were plotted against predicted values (Figure 4), the scatter plot did not show any noticeable pattern. Most of the standardized residuals were distributed along but close to the horizontal line (zero), indicating the attainment of homoscedasticity and the model fitted well the data.

Table 5. Height models showing parameter values and performance

Model No.	Parameter estimate and standard error			Goodness of fit		
	b_0	b_1	b_2	R^2	RMSE	AIC
1	3.3266 (0.3466)	0.1306 (693576.1)	-	0.77	1.79	165.09
2	1.3 (0)	0.3923 (0.0241)	-0.00171 (0.00063)	0.72	2.03	200.20
3	2.3249 (0.8977)	6.6101 (5.4716)	0.2847 (0.0241)	0.78	1.79	164.37
4	2.61e+08 (0)	1.0e+09 (0)	-3.3266 (0)	0.77	1.79	165.06

Note: b_0: constant; b_1: intercept for independent variable DBH, and b_2: constant parameters of models, and the numbers in blackest are their standard errors

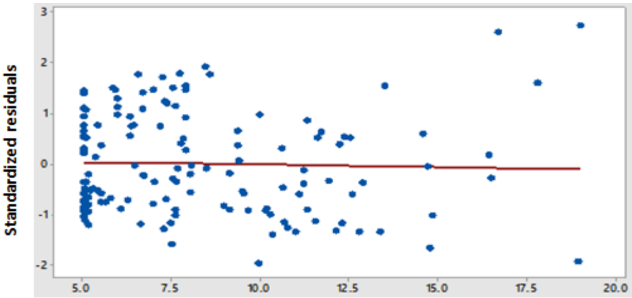

Figure 2. Distribution of residuals from the horizontal line for height model 3

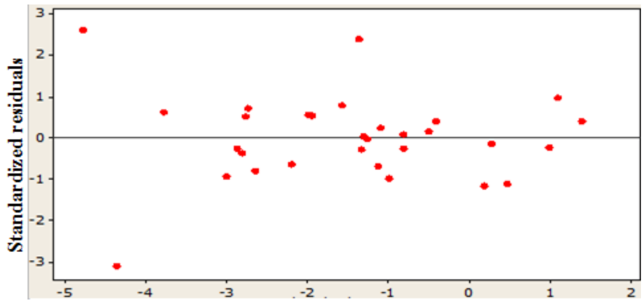

Figure 3. The distribution of residuals from line zero for the volume model 3

Table 6. Volume models showing parameter values and performance

Model No.	Parameter estimates					Goodness of fit				Accuracy
	a	b	c	d	e	CF	R^2	RMSE	AIC	%BIAS
1	-10.02 -1.28^s 0.000^p	0.7 0.8 0.383^p	0.2171 0.158^s 0.179^p	2.741 1.12^s 0.022^p	-0.402 0.26^s 0.14^p	1.043	0.97	0.292	61.2	0.
2	-9.86 0.30^s 0.000^p	0.99 0.04 0.000^p				1.043	0.97	0.292	-111.18	-1.14
3	-9.845 0.30^s 0.000^p	1.9 0.1 0.000^p	1.089 0.16^s 0.000^p			1.044	0.97	0.296	-144.18	-2.27
4	-9.583 0.48^s 0.000^p	2.63 0.15 0.000^p				1.118	0.91		-138	2.

Note: a is intercept, b, c, d, and e are constant parameters, and the superscript "s" and "p" are the standard error and probability of a parameter, respectively

Discussion

The height and diameter relationship found in this study was non-linear. Non-linear regression model 3 had a higher R^2 than the other models tested. Marshall et al. (2012) argued that individual tree height is not simply correlated with diameter; instead, the ratio is related to species and the condition of the area. Differences in the structure "architecture" of the woody plants, especially shrubs, might have affected the performance of the height models tested.

The developed volume and biomass models were important for assessing volume and carbon stock in LFR. However, the models tested performed differently. For both volume and biomass, model 3, which included height (Ht) in addition to (DBH) as independent variables, improved the fit more than when (DBH) alone (Model 4). Marshall et al. (2012) reported an overestimation of 55 t ha^{-1} or 31.5% biomass when height was excluded in the biomass prediction model. That is in agreement with other studies (Malimbwi et al. 1994; Chave et al. 2005, Marshall et al. 2012; Mugasha et al. 2013; Mwakalukwa et al. 2014) that argued regression equations incorporating height are most likely to be accurate as they incorporate more information on the size of stems than those which utilized diameter alone. It was further shown that the inclusion of wood basic density in model 5 significantly improved the fit as supported by higher R^2 and low RMSE.

Table 7. Biomass models showing parameter values and performance

Model No.	Parameter estimates a	b	c	d	e	CF	Goodness of fit R^2	RMSE	AIC	Accuracy %BIAS
1	-3.029 1.37^s 0.037^p	0.445 0.93^s 0.638^p	0.2217 0.16^s 0.201^p	3.384 1.21^s 0.01^p	-0.589 0.28^s 0.056^p	1.051	0.96	0.315	180.43	3.21
2	-2.074 0.33^s 0.000^p	0.853 0.039^s 0.000^p				1.054	0.95	0.325	257.28	-3.36
3	-2.05 0.33^s 0.000^p	1.585 0.16^s 0.000^p	1.01 0.18^s 0.000^p			1.054	0.95	0.326	236.81	-2.31
4	-1.807 0.48^s 0.001^p	2.251 0.15^s 0.000^p				1.117	0.89	0.47	201.54	1.33
5	-1.666 0.31^s 0.000^p	0.853 0.04^s 0.000^p				1.054	0.95	0.324	224.13	-1.93

Note: The superscript "s" and "p" are the standard error and probability of a parameter, respectively

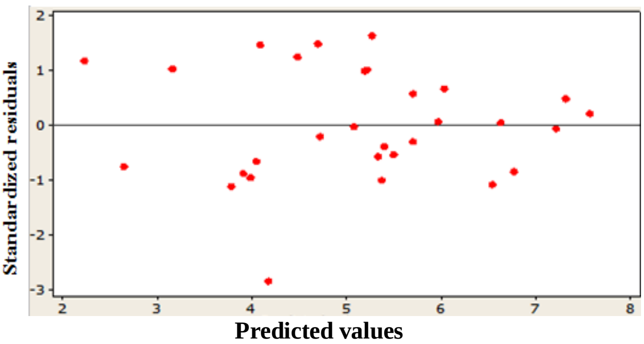

Figure 4. The distribution of residuals about the horizontal line for biomass model 5

The higher diversity and species composition experienced in the tropical forests, particularly the dry evergreen montane forest of LFR, support the argument for developing site-specific equations for mixed species (Djomo et al. 2016; Mokria et al. 2018; Asrat et al. 2020). Furthermore, Mwakalukwa et al. (2014) argued that due to the variation in species composition from site to site and the impact of site conditions on the shape of trees, the use of mixed-species regression models calibrated using data from sites with similar conditions and species composition is a logical choice. However, using biomass-generalized allometric equations available for tropical forests (Brown et al. 1989; Chave et al. 2005; Djomo et al. 2016) gave lower results and tended to give higher errors (Teshome et al. 2022). For instance, Brown et al. (1989) biomass model gave an error of 5.5%, while that of Chave et al. (2005) had a much higher error of 15.1%, implying that site-specific mixed species biomass models developed in this study are more accurate by having a much lower error of 1.93% in the prediction.

The differences in the estimates might also be attributed to differences in diameter size classes used to construct these generalized models. For instance, Brown et al. (1989) used a maximum of 40 cm. In contrast, this study developed the volume and biomass models with a maximum diameter of 58.5 cm. Moreover, locally abundant species are not represented in the databases used to develop the generalized models, thus failing to accurately predict the true biomass estimates in a particular forest (Mugasha et al. 2013; Mwakalukwa et al. 2014; Mugasha et al. 2016a). Therefore, caution should be taken when using generalized models where local site-specific mixed-species models are unavailable (Djomo et al. 2016; Teshome et al. 2022). The use of site-specific models is recommended to ensure that high precision in the quantification of woodland resources is achieved (Mwakalukwa et al. 2014; Njana 2017; Mauya et al. 2019).

In the allometric models selected for height prediction, the volume and biomass (carbon) quantification had high R^2 and lower RMSE, AIC, and percentage bias than the existing generalized equations developed for vegetation in dry tropical forests. This study showed that height model 3, volume model 3, and biomass model 5 were the best-predicting models in the study area. Despite DBH being the common predictor variable in most developed allometric models, the inclusion of height in the volume equation, and the use of wood density in biomass model 5 increased the goodness of fit (Henry et al. 2010; Mugasha et al. 2013; Mwakalukwa et al. 2014). The developed models provide important managerial tools that will assist managers, planners, and policymakers manage the LFR more sustainably, especially for future REDD+ project implementation phases in Tanzania.

In conclusion, this study, for the first time, reports volume and biomass models for dry evergreen montane forests found in Tanzania. The reported site-specific models developed based on destructively sampled trees data from dry evergreen montane forests in Northern Tanzania yielded low bias, indicating an excellent fit. These models may also be considered for application in other dry evergreen montane forests lacking site-specific models after carefully evaluating the required conditions (i.e., tree-size distribution, species composition, and site characters). These developed models add to the knowledge about volume and biomass models developed from various vegetation types found in Tanzania.

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