



Modelling and quantifying tree biometric properties of dry Afromontane forests of south-central Ethiopia

Zerihun Asrat^{1,2} · Tron Eid¹ · Terje Gobakken¹ · Mesele Negash²

Received: 25 October 2019 / Accepted: 15 July 2020 / Published online: 9 August 2020
© The Author(s) 2020

Abstract

Key message Models for quantifying tree biometric properties, imperative for forest management decision-making, including height, diameter, bark thickness and volume were developed, and wood basic density was documented for dry Afromontane forests of south-central Ethiopia.

Abstract Tree biometric properties such as height (ht), diameter at breast height (dbh), bark thickness (bt), volume and wood basic density (wbd) are imperative for forest management decision-making. For dry Afromontane forests in south-central Ethiopia, models for quantifying such tree properties are totally lacking. This study, therefore, aimed at developing models for ht based on dbh, for dbh based on stump height diameter (dsh), for bt based on dbh, for volume based on dbh, ht and crown width (crw), as well as documenting wbd data. Comprehensive and representative datasets were collected from Degaga–Gambo and Wondo Genet forests. The ht, dbh and bt modelling were based on 1345 sampled trees during forest inventories, while the volume modelling and wbd documentation were based on 63 destructively sampled trees from 30 species covering 87% of the total basal area in the study sites. Weighted least squares regression was applied for modelling and leave one out cross-validation was used for evaluation. The ht–dbh and dbh–dsh models performed well (pseudo- $R^2 = 0.72$ and 0.98), while bt–dbh performed poorer (pseudo- $R^2 = 0.42$). Models for the total tree, merchantable stem and branches volume were developed with different options for independent variables, where pseudo- R^2 varied from 0.74 to 0.98, with smallest values for the branches models. The models may be applied to forests outside the present study sites provided that the growing conditions are carefully evaluated. The species-wise wbd was ranging from 0.426 to 0.979 g cm⁻³, with the overall mean of 0.588 g cm⁻³. The wbd data will be useful for building up a national wbd database and may also be included in the Global Wood Density database. The study represents a significant step towards sustainable forest management including REDD + MRV practices in the dry Afromontane forests of south-central Ethiopia.

Keywords Dry Afromontane forests · Height–diameter and bark models · Volume models · Wood basic density

Introduction

Forest management decisions can be affected by the availability of relevant tree biometric information. In the course of acquiring information for decision-making in the whole

continuum from single trees to forests, the use of appropriate models and data plays an immense role (Vanclay 1994; van Laar and Akça 2007). The availability of tree biometric data like wood basic density (wbd), tree height (ht), diameter at breast height (dbh), bark thickness (bt), volume and biomass are critical for supporting forest management decision-making and reducing costs for ground based forest resource assessment (van Laar and Akça 2007; West 2009). Such data and models are also the basis for assessing changes over time, which is linked to a successful implementation of measurement reporting and verification (MRV) practices in reducing emissions from deforestation and forest degradation (REDD+) programs (Penman et al. 2003).

Diameter at breast height and tree height are core variables describing trees. In the tropics, tree height measurement

Communicated by Braeuning.

✉ Zerihun Asrat
zerihun.asrat.kutie@nmbu.no; zerasrat@gmail.com

¹ Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, 1432 Ås, Norway

² Wondo Genet College of Forestry and Natural Resources, P.O. Box 128, Shashemene, Ethiopia

is very challenging compared to dbh (Mokria et al. 2015). Hence, tree height is mostly determined by means of models describing ht–dbh relationships (West 2009; Mugasha et al. 2013, 2019; Mokria et al. 2015). To this line, studies have also reported 10–30% errors in ht measurements in tropical forests (Larjavaara and Muller-Landau 2013). Hence, the presence of appropriate ht–dbh models may, therefore, reduce both the inventory costs and the uncertainty in height estimates, especially in tropical forests with complex tree architecture (Feldpausch et al. 2011). When assessing previous harvests or damages in a forest, only stump diameter (dsh) can usually be measured. For such cases, it is, therefore, important to establish a dbh–dsh relationship, where dbh, and subsequently volume or biomass can be estimated by measuring dsh only (Corral-Rivas et al. 2007; Özçelik et al. 2010). Furthermore, quantifying bark thickness of trees by means of an established bt–dbh relationship might be useful either to assess the volume of solid wood to be used for construction materials or volume of bark to be used for energy purposes, spices or medicine (van Laar and Akça 2007; Kershaw et al. 2017).

Volume data are used to describe present forest resources, as a variable in growth and yield models for predicting future growing stocks and impacts of harvest as well as to assist in evaluating silvicultural practices (Vanclay 1994; Weiskittel et al. 2011). Volume data may also be used to determine biomass using expansion and conversion factors (Lindner and Karjalainen 2007; Bollandsås et al. 2016). Models predicting volume of trees based on dbh, ht and other tree properties measured in the field have been developed for decades. The development of such models, however, continues to attract attention, because no single theory exists for developing volume models that can be used satisfactorily for all tree species and forest types (Muhairwe 1999).

Wood basic density (g cm^{-3}) of trees, i.e. the ratio of oven dry mass to the green volume of the wood (Williamson and Wiemann 2010), is the basis for characterizing tree species from a wood utilization point of view (Chave et al. 2009; Missanjo and Matsumura 2016). Information on wbd may have management implications since larger wbd indicates better wood quality for fuel (Githiomi and Kariuki 2010) and better resistance to severe abiotic disturbance factors (Chave et al. 2009). Wood basic density may also be used to predict biomass either when using allometric models (Chave et al. 2014; Njana et al. 2016) or along with biomass expansion factors and volume data (Bollandsås et al. 2016). The magnitude of wbd is reported to vary with tree height and age (Githiomi and Kariuki 2010), tree section (Njana et al. 2016; Tesfaye et al. 2019), and between species, sites, and other environmental factors (Henry et al. 2010; Ubuy et al. 2018a).

The present study was conducted in dry Afromontane forest, which is a dominant forest type in Ethiopia (UN-REDD 2017). Dry Afromontane forests are characterized by high

levels of biodiversity and species endemism (Mittermeier et al. 2004; Friis et al. 2010) and are found in most highland areas in north-central, central and south-central parts at elevations between 1500 and 3400 m. Having about 460 woody species recorded, the dry Afromontane is the second most diverse forest type in the country following the *Acacia-Commiphora* forest (Friis et al. 2010). The upper canopy of the remaining patches of these forests are dominated by *Juniperus procera*, *Afrocarpus falcatus*, *Olea europaea*, *Croton macrostachyus* and *Ficus species*, while the middle and lower canopy are usually occupied by *Allophylus abyssinicus*, *Apodytes dimidiata*, *Bersama abyssinica*, *Cassipourea malosana*, *Celtis africana*, *Chionanthus mildbraedii*, and *Dombeya torrida* (Friis et al. 2010).

Forests in Ethiopia and their management have been given attention recently from different stakeholders, mainly in line with the growing concern on climate change and its mitigation issues (UN-REDD 2017). In response, the country is striving to improve its forest management by implementing new approaches like participatory forest management (PFM) (Lemenih et al. 2015), area exclusions (Lemenih and Kassa 2014), and REDD+ (UN-REDD 2017). Dry Afromontane forests, like most other natural forest types in the country, have none or little active management (Guillozet et al. 2014). However, recently, the longstanding concern that such forests should be managed and used sustainably rather than mere protection is gaining momentum, and thus some efforts to implement PFM regimes which integrate sustainable timber harvesting have been seen (Lemenih et al. 2015; Ayele et al. 2018). This may provide sufficient incentives and motivate to a better forest management scheme, as opposed to the status-quo protection-oriented system, which favours illegal and uncontrolled harvests of timber and other forest products (MEFCC 2018). The forest policy amendment in 2018 and the development of guidelines for sustainable timber harvesting from forests under PFM (Ayele et al. 2018) are steps forward towards a shift in management.

Models and data which are basic for informed decision-making and facilitating a shift in forest management for dry Afromontane forests in Ethiopia, however, are very scarce or totally lacking. Kebede et al. (2013) and Wondrade et al. (2015), for example, spent much time measuring both dbh and ht of all trees in their study area due to lack of any models describing ht–dbh relationships. No studies have been found specifically dealing with the dbh–dsh relationship, although several studies from natural forests in Ethiopia have used dsh instead of dbh to estimate biomass (e.g. Mokria et al. 2018; Ubuy et al. 2018b). Except for Eriksson et al. (2002), who partly dealt with bark from a fire resistance point of view, no studies have been found quantifying bt of trees in Ethiopia. Despite having diverse forest types, models estimating tree volume for natural forests in Ethiopia are lacking (Henry et al. 2011). In the literature, we

found volume models only for plantations (Pohjonen 1991; Teshome 2005; Berhe 2009). Hence, a general volume formula that uses tree basal area, ht and form factor (f) has been applied. Form factor is a correction value that characterizes the shape of the tree stem and adjusts the assumed cylindrical volume value to the actual stem volume (Laar and Akça 2007). However, this approach requires knowing species-specific f values, which are totally lacking for natural forests in Ethiopia. Instead, a generalised f value of 0.5 is usually applied (Sisay et al. 2017). Despite the importance of wbd in describing wood properties and the presence of the high number of tree species as well as diverse environmental conditions in Ethiopia, only a limited number of wbd studies are found in the literature (Desalegn et al. 2012; Ubuy et al. 2018a; Tesfaye et al. 2019). As a result, biomass estimations in the Ethiopian forest reference level (FRL) report submitted to the United Nations Framework Convention on Climate Change (UN-REDD 2017) were based on wbd values obtained from the Global Wood Density (GWD) database (Chave et al. 2009; Zanne et al. 2009), comprising very little data from Ethiopia.

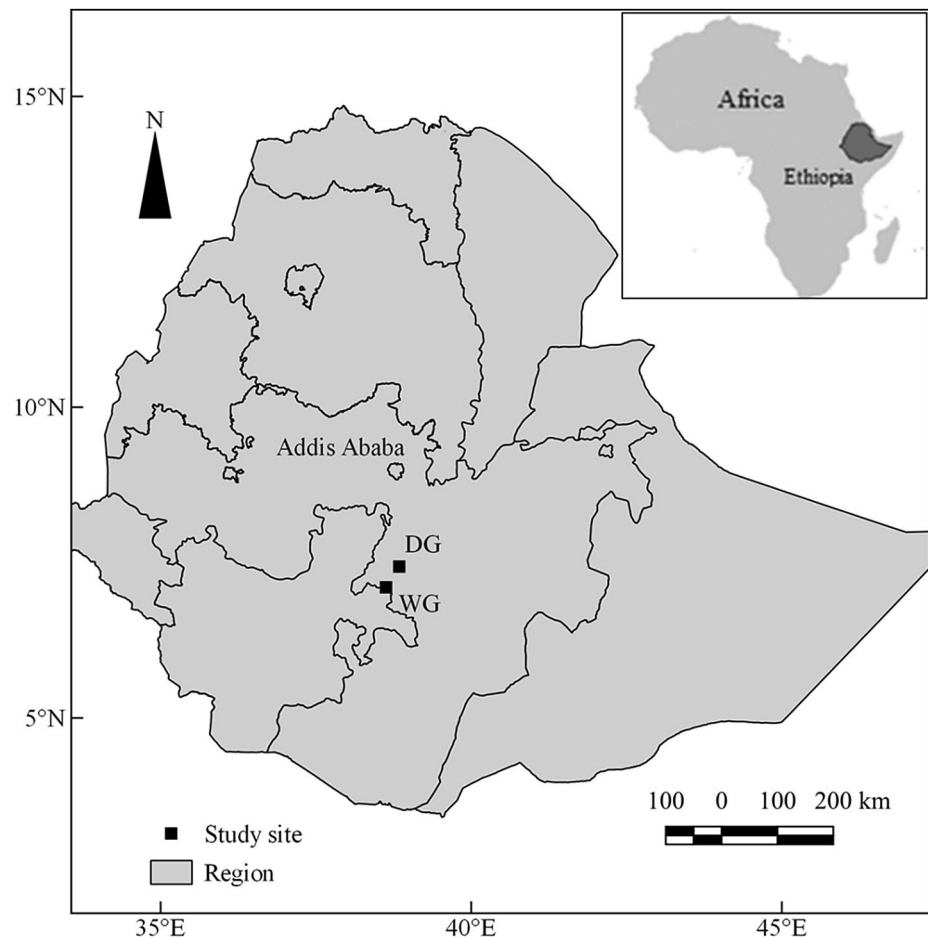
The main objective of this study was, therefore, to provide models and data that can be used as tools for quantifying biometric tree properties and facilitating a sustainable use of resources in the dry Afromontane forests of south-central Ethiopia. Specifically, the study aimed at (1) developing models for ht based on dbh, dbh based on dsh and bt based on dbh, (2) developing models for merchantable stem, branches and total tree volume, and (3) determining and documenting the wbd values and their variability for different tree species.

Materials and methods

Study sites

The study was conducted in Degaga–Gambo and Wondo Genet dry Afromontane forests in south-central Ethiopia (Fig. 1), situated along the eastern escarpment of the Great East African Rift Valley. The sites receive a biannual rainfall with the short rainy season between March and May and the main rainy season between July and September.

Fig. 1 Map of study sites; *DG* Degaga–Gambo, *WG* Wondo Genet



The surrounding landscapes are composed of mosaics of land use/land covers including plantations, woodlands, settlements and water bodies. The sites are habitat for several wildlife species and source of several tributary rivers. The vegetation at both sites is remnant of previously dense dry Afromontane forests (Friis et al. 2010).

In Degaga–Gambo, the district authorities simply conserve the natural forests, while maintaining plantation forests of exotic tree species for economic wood production purposes. During the forest inventory, we observed many stumps from illegal harvesting in the natural forests. Currently, there is an ongoing effort of transferring the natural forests into a PFM system as a means to reduce deforestation and forest degradation in the area. Degaga–Gambo forest extends from 38°45′ to 38°56′ E longitude and from 7°13′ to 7°33′ N latitude, with an area of 12,580 ha. The elevation ranges from about 2100 to 2700 m a.s.l. The mean annual rainfall and temperature are 1245 mm and 14.9 °C, respectively. The soils are generally classified as Mollic Nitisols and Humic Umbrisols, respectively, at lower and upper altitudes (Fritzsche et al. 2007). The Wondo Genet site is under the concession areas of Wondo Genet College of Forestry and Natural Resources, which gives the forest protection and guarding services against illegal logging and fire incidences. The natural forest has no management plan, and no silvicultural interventions are carried out except some occasional planting activities. It extends from 38°37′ to 38°39′ E longitude and from 7°6′ to 7°7′ N latitude. The forest has an area of 390 ha with an altitudinal range from about 1850 to 2400 m a.s.l, and the soils are mainly classified as Mollic Andosols (Erikson and Stern 1987). The mean annual rainfall and temperature are 1123 mm and 17.6 °C, respectively.

Data collection

Forest inventories

Forest inventories were carried out in 2018 to obtain information required for the tree selection in the destructive

sampling (e.g. Mauya et al. 2014). A systematic square grid was overlaid with the sampling frame (map of the respective sites) that resulted in 65 and 42 sample plots for Degaga–Gambo and Wondo Genet, respectively. Circular plots with a size of 1000 and 400 m² were used for the inventories in Degaga–Gambo and Wondo Genet, respectively. All trees in the plot with dbh ≥ 5 cm were identified by species and measured for dbh. Up to ten trees were then randomly sampled for each plot and measured for dsh (at 0.30 m above ground), ht, and bt (at breast height). Where there were only ten or less trees in the plot, all trees were measured for dbh, dsh, ht and bt. For buttressed trees, dsh was measured at the top of the buttress, and then dbh measured 0.3 m above this point if the buttress extended beyond 1 m (West 2009). Tree diameters were measured using diameter tape or calliper, while ht was measured using a Haglöh VL5 hypsometer. For the sample plots, 45 and 50 tree species were identified in Degaga–Gambo and Wondo Genet, respectively, while in total there were 71 tree species. The maximum dbh encountered was 270 cm for Degaga–Gambo and 197 cm for Wondo Genet. A total of 1345 sample trees representing 60 tree species were measured and used for modelling of ht, dbh and bt. The mean (and range) values of these trees were 24.7 cm (5.0–270.0 cm), 20.9 cm (5.0–270.0 cm), 10.9 m (2.1–69.4 m) and 9.9 mm (2.0–50.0 mm) for dsh, dbh, ht and bt, respectively.

Selection of trees for destructive sampling

Based on the forest inventory data, a total of 63 trees representing 30 species (11 unique from each site and eight common from both) were selected for destructive sampling (Tables 1, 8 in Appendix). The dominant tree species, that constituted about 85% of the total basal area, were first included into the sample proportional to their basal area. The remaining trees were selected randomly among all species, meaning that 87% of the total basal area was represented in the dataset. An effort was made to proportionally select the trees throughout the 11 diameter classes considered from 5

Table 1 Descriptive summary of destructively sampled trees

	Both sites (n = 63)			Degaga–Gambo (n = 32)			Wondo Genet (n = 31)		
	Mean	Range	SD	Mean	Range	SD	Mean	Range	SD
dbh (cm)	37.8	7.0–106.5	29.9	37.4	7.0–105.5	30.0	38.3	8.0–106.5	30.3
ht (m)	17.9	5.2–38.8	9.1	17.6	5.4–36.0	8.9	18.2	5.2–38.8	9.4
crw (m)	8.4	2.4–23.9	5.0	7.9	2.3–20.0	4.7	8.9	2.4–23.9	5.3
V _{tot} (m ³)	3.066	0.014–22.537	5.230	2.897	0.014–17.252	4.918	3.242	0.031–22.537	5.611
V _{ms} (m ³) ^a	2.687	0.074–11.865	3.559	2.683	0.076–11.865	3.671	2.691	0.074–11.579	3.525
V _{br} (m ³)	1.147	0.014–10.958	2.140	0.969	0.014–6.113	1.654	1.332	0.031–10.958	2.564

SD = standard deviation

^aV_{ms} for trees with dbh ≥ 15 cm only, n = 23, 22 and 45 for Degaga–Gambo, Wondo Genet and both sites, respectively

to ≥ 105 cm (i.e. 5–15, 15–25, ..., ≥ 105), as this will help to ensure better and more stable models (Bollandsås et al. 2016). In addition, we tried to have a fair representation of large trees (10 trees with dbh > 75 cm) to try to avoid extrapolation in model applications (Bollandsås et al. 2016). Moreover, during destructive sampling, efforts were made in the selection to represent the altitudinal variation and spatial coverage over both sites to capture as much variability as possible in tree properties.

Before felling, we measured dbh over bark with a diameter tape or a calliper, depending on the size and shape of the stem. Tree height was measured with Haglöf VL5 hypsometer. In addition, mean crown width (crw) was recorded by taking two measurements using a measuring tape, one for maximum and one for minimum crown width. At the position of each tree, elevation (m), slope (%) and aspect (N, E, S, W) were measured, and basal area ($\text{m}^2 \text{ha}^{-1}$) was determined by means of relascope. Our hypotheses regarding wbd were that slope and basal area positively affect wbd because of slower growth, while elevation negatively affects wbd because precipitation increases with elevation and hence growth will be faster. In contrast, north and south facing aspects affect wbd positively and negatively, respectively, because of slower and faster growth.

Destructive sampling procedures

The selected trees were felled at stump height (0.3 m) using a chainsaw and each tree was sorted into merchantable stem, branches, and leaves and twigs sections (Table 1). The main stem up to the minimum useable top diameter (≥ 10 cm) was considered as merchantable stem. This cut off point was applied since it has been practiced as a rule of thumb at the sawmill of Wondo Genet College of Forestry and Natural Resources. However, trees with dbh < 15 cm were included in the branches section since they are considered to have insignificant merchantable value. As a result, the merchantable stem volume analysis was based on 45 out of the 63 trees (Table 1). The branches section included the top log with diameter < 10 cm and all branches with diameter ≥ 2 cm. Twigs with diameter < 2 cm were set aside together with leaves for a separate biomass study. The stem was cross-cut into shorter logs (from 0.5 to 2.5 m) to facilitate the mid diameter and length measurement as well as to reduce taper effects. Similarly, branches were cut into pieces mostly shorter than 2 m and measured for length and mid diameter. The volume of each log was determined by multiplying the middle cross-sectional area of the log by its length (e.g. Bollandsås et al. 2016). Tree merchantable stem volume (V_{ms}) and branches volume (V_{br}) were obtained by summing up volumes for all logs in each section, respectively. Total tree volume (V_{tot}) was determined by summarizing merchantable stem and branches volumes (Table 1; Fig. 3 in appendix).

Sub-samples for wood basic density and laboratory work

For determining wbd, Chave et al. (2006) recommended collecting wood sub-samples from all parts of the tree. Accordingly, for each tree, we collected three wood discs from the stem (i.e. one from breast height position, and one from each of the middle and upper parts) and three wood discs from the branches (one disc at a random point from a small, medium and large branch, respectively). The sizes of most discs were about 3–4 cm in length. For smaller trees with few and small-sized branches, only one sub-sample was collected for the branch section. For larger trees, where it was not practical to take the whole wood disc, sub-samples were taken in such a way that they represent both the sapwood and heartwood sections (Williamson and Wiemann 2010). In total, we collected 364 sub-samples of wood, which correspond to an average of 5.8 sub-samples per tree. All sub-samples were put in an airtight plastic bag and brought to a laboratory, where green volumes were determined by the water displacement method after peeling off the bark. Then the sub-samples were oven dried at a temperature of about 103 °C until a constant mass was guaranteed by checking through recurrent measurements with a sensitive digital balance. Often this was attained within 48 or 72 h, depending on the size of the sub-sample. Finally, wbd was determined as the ratio of dry mass (g) to the green volume (cm^3) for each sub-sample.

Data analyses

All data analyses were done with the R software (R Core Team 2019). The ‘nlstools’ package (Baty et al. 2015) in the R software was used for non-linear regression. Model fitting and performance evaluation were carried out based on two different datasets. To develop the ht–dbh, dbh–dsh and bt–dbh relationships, we used the sample trees’ data ($n = 1345$) from the inventories. To develop models for V_{tot} , V_{ms} and V_{br} , and to document wbd values and their variability, we used the destructively sampled trees ($n = 63$).

For establishing the ht–dbh relationship, five different non-linear models were tested. The data were first divided randomly into equal sized training and test datasets. Models were fitted to the training dataset, then applied on the test dataset for evaluation. Their performances were assessed using root mean squared error (RMSE), mean prediction error (MPE) and pseudo- R^2 (Eq. 7–11), where generally the smallest (close to zero) RMSE and MPE values and largest pseudo- R^2 values (close to 1), indicating a better model fit (James et al. 2013). The best performing model was finally recalibrated to the full dataset. The dbh–dsh and bt–dbh models were developed in a similar way as ht–dbh model.

For volume modelling, the data were first visually explored by plotting volume against the potential

explanatory variables (Fig. 3 in appendix) to examine their functional relationships. Several textbooks suggest the use of dbh and ht together or separately as independent variables in volume modelling (e.g. West 2009; Kershaw et al. 2017). We were not able to find volume models developed for natural forests in Ethiopia, hence potential models for further testing were picked from the general literature (Schumacher and Hall 1933; van Laar and Akça 2007; West 2009) and from previous research on tree volume in natural forests in Tanzania (Mauya et al. 2014; Mugasha et al. 2016) and Malawi (Kachamba and Eid 2016). In addition, we tested two models for prediction of V_{br} , where crw was included as independent variable. The following six models were tested:

$$V_{tot,ms,br} = a + b \times (dbh)^2, \quad (1)$$

$$V_{tot,ms,br} = a \times (dbh)^b, \quad (2)$$

$$V_{tot,ms,br} = a \times (dbh^2 \times ht)^b, \quad (3)$$

$$V_{tot,ms,br} = a \times (dbh)^b \times (ht)^c, \quad (4)$$

$$V_{br} = a \times (dbh^2 \times crw)^b, \quad (5)$$

$$V_{br} = a \times (dbh)^b \times (crw)^c, \quad (6)$$

where a , b , and c are model parameters.

Weighted ordinary least square regression was applied for Model 1 and non-linear least square regression for the remaining. Weights were applied to account for heteroscedasticity in the data, i.e. non-constant variance of the residuals with increasing values of the response variable. This is a common phenomenon that often occurs when modelling biological entities like trees (van Laar and Akça 2007; Zeng and Tang 2011). The error variances were inversely proportional to the dbh^2 , and hence a weight of $1/(dbh^w)^2$ was used, where w is the weighting factor. The initial value for w was determined as explained in Picard et al. (2012), and finally after an iterative procedure the value which resulted in the smallest possible prediction error was selected as weighting factor. In addition, following recommendations by Kelly and Beltz (1987) for models with dbh and ht as independent variables, a weighting factor of $1/(dbh^w \times ht)^2$ was tested, and the obtained prediction error was compared with the prediction error of $1/(dbh^w)^2$. Eventually, the one with the smallest prediction error was used for weighting.

The basic requirement when testing the models was that all parameter estimates should be significantly different from zero. For further evaluation of the model performances, a leave one out cross-validation approach was applied (James

et al. 2013), where one observation was put aside as test data and the model fitted to all remaining observations (i.e. $n - 1$, training data) and then prediction was done on the test data ($n = 1$) at a time. The procedure was repeated n times until all observations in the data were tested. The residuals, difference between the observed and predicted, were then used to calculate the performance indicators RMSE, RMSE%, MPE, MPE% and pseudo- R^2 as shown in Eq. 7–11, respectively. Akaike information criterion (AIC) was also computed.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n}}, \quad (7)$$

$$RMSE (\%) = \left(\frac{RMSE}{\bar{Y}} \right) \times 100, \quad (8)$$

$$MPE = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)}{n}, \quad (9)$$

$$MPE (\%) = \left(\frac{MPE}{\bar{Y}} \right) \times 100, \quad (10)$$

$$\text{pseudo-}R^2 = 1 - \left(\frac{SSR}{CSST} \right), \quad (11)$$

where Y_i and \hat{Y}_i are observed and predicted ht, dbh, bt or volume (either total, merchantable stem or branch) of observation i respectively; \bar{Y} is mean observed ht, dbh, bt or volume (either total, merchantable or branch); SSR is sum of squared residuals; and CSST is corrected total sum of squares.

We also investigated consequences of using form factors in determining total volume by means of Eq. 12;

$$V_{tot} = g \times ht \times f_{0.5, \text{mean}, \text{pred}}, \quad (12)$$

where g is the basal area of a tree calculated using dbh; $f_{0.5}$, f_{mean} and f_{pred} are different form factors. We first applied the frequently used form factor of 0.5 ($f_{0.5}$) and the mean form factor observed in our data (f_{mean}). The f_{mean} is the average of all observed form factors calculated as the ratio of observed total volume and the volume of a cylinder with a diameter dbh and length of ht. In addition, we wanted to test the application of a predicted form factor (f_{pred}) for each tree by fitting a model based on dbh and ht (Tenzin et al. 2016) to the observed form factors in our data. However, this approach failed because of insignificant parameter estimates in the model. Finally, since no previously developed relevant volume models exist for Ethiopia, the performance of some previously developed models for natural forests elsewhere in east-Africa (Mauya et al. 2014; Kachamba and Eid 2016; Mugasha et al. 2016) were tested on our dataset.

The wbd values obtained from stem and branch sub-samples were averaged to get mean stem and branch wbd. These mean values were further aggregated by weighting them by their respective volumes to obtain a volume-weighted wbd at tree and species level. The wbd data were organized and summarized using descriptive statistics. In addition, analysis of variance was carried out to assess the presence of significant variations in wbd among the tree species and between the sites. Differences among stem sections (breast height, middle and upper stem positions) and branch sizes (big, mid and small branch) for wbd were also tested by means of analysis of variance. Furthermore, pair-wise t tests were applied to determine if there were significant wbd differences between stems, branches, values at breast height and volume-weighted means. As wbd is expected to vary depending on growing conditions, we fitted a linear regression to explore effects of elevation (m), slope (%), aspect (N, E, S, W) and basal area (m² ha⁻¹) on wbd variations.

Results

The model parameters and model performance indicators for the relationships between ht–dbh, dbh–dsh and bt–dbh are shown in Table 2. The ht–dbh relationship was relatively strong (pseudo-*R*² = 0.72). A very strong dbh–dsh relationship was found (pseudo-*R*² = 0.98) while the bt–dbh relationship was weaker. Generally, none of the MPEs for the models were significantly different from zero.

The model parameters and performance indicators for the general total (GT), merchantable stem (GMS) and branch (GB) volume models are shown in Table 3. The pseudo-*R*² of the total volume and merchantable stem volume models varied between 0.93–0.95 and 0.96–0.98, respectively. Moreover, none of these models had MPEs significantly different from zero and all had significant model parameters. For total volume, Model GT2 performed best (pseudo-*R*² = 0.95, RMSE = 37.4%) for the models with only dbh as independent variable, while Model GT3 performed best

Table 2 Model parameters and performance indicators for different tree variable models

Tree variable	Model	Parameters			Pseudo- <i>R</i> ²	RMSE		MPE	
		<i>a</i>	<i>b</i>	<i>c</i>		(^A)	(%)	(^A)	(%)
ht	ht = 1.3 + <i>a</i> × [1 – exp(– <i>b</i> × (dbh) ^{<i>c</i>})]	41.498221	0.023370	0.849478	0.72	3.96	36.4	–0.01	–0.1
dbh	dbh = <i>a</i> × (dsh) ^{<i>b</i>}	0.6720320	1.062245		0.98	3.36	16.1	0.14	0.7
bt	bt = <i>a</i> × (dbh) ^{<i>b</i>}	2.4743200	0.489150		0.42	4.90	49.7	0.00	0.0

^ARMSE and MPE in cm, m and mm for dbh, ht and bt, respectively; *n* = 1345; all parameters *p* < 0.001

Table 3 Model parameters and performance indicators for general total, merchantable stem and branch volume models

Tree section	Model	Parameters			Pseudo- <i>R</i> ²	RMSE		MPE		AIC
		<i>a</i>	<i>b</i>	<i>c</i>		(m ³)	(%)	(m ³)	(%)	
Total volume (<i>n</i> = 63)	GT1	–0.1591000	0.0014030		0.93	1.326	43.2	–0.0027	–0.1	199
	GT2	0.0001228	2.5500000		0.95	1.146	37.4	–0.0004	–0.0	187
	GT3	0.0000605	0.9789000		0.95	1.156	37.7	–0.0009	–0.0	193
	GT4	0.0000891	2.4090000	0.2795000 ^a	0.95	1.158	37.8	0.0053	0.2	187
Merchantable stem volume (<i>n</i> = 45)	GMS1	–0.2715391	0.0009319		0.96	0.675	25.2	–0.0024	–0.1	86
	GMS2	0.0000954²	2.5020000		0.98	0.518	19.3	0.0017	0.1	67
	GMS3	0.0000369 ¹	0.9811000		0.97	0.642	23.9	–0.0006	–0.0	85
	GMS4	0.0000596²	2.2480000	0.4701000²	0.98	0.557	20.7	0.0008	0.0	68
Branch volume (<i>n</i> = 63)	GB1	–0.0036570*	0.0004964		0.78	0.997	86.9	0.0036	0.3	179
	GB2	0.0000663¹	2.4660000		0.74	1.079	94.1	0.0019	0.2	178
	GB3	0.0000421¹	0.9227000		0.74	1.085	94.5	0.0721	6.3	177
	GB4	0.0000771*	2.7130000	–0.3671000*	0.72	1.124	98.0	0.0054	0.5	179
	GB5	0.0000423 ¹	0.9829000		0.88	0.752	65.5	–0.0056	–0.5	129
	GB6	0.0000773¹	1.4980000	1.5070000	0.89	0.714	62.2	0.0020	0.2	120

Best performed models shown in bold

*Non-significant parameter (*p* > 0.05); ¹*p* < 0.05; ²*p* < 0.01; all other parameters *p* < 0.001

(pseudo- $R^2=0.95$, RMSE=37.7%) for the models with both dbh and ht as independent variables. Likewise, for merchantable stem volume, Model GMS2 and GMS4 with dbh only and with dbh and ht independent variables, respectively, were performing best regarding pseudo- R^2 and RMSE. In general, the addition of ht into the total and merchantable stem volume models did not improve the performance indicators. The branch volume models in general had larger RMSEs compared to the total and merchantable stem volume models. For the models with dbh only as independent variable, Model GB2 was found to perform best (pseudo- $R^2=0.74$, and RMSE=94.1%). Models with dbh and ht predictor variables either had poorer performance (Model GB3) or insignificant parameter estimates (Model GB4). Inclusion of crw instead of ht reduced the RMSEs to some extent. For the models with dbh and crw as independent variables, Model GB6 was found to perform best (pseudo- $R^2=0.89$, RMSE=62.2%). None of the branch volume models had MPEs significantly different from zero.

Site-specific total volume models for Degaga–Gambo (DT) and Wondo Genet (WT) were also developed (Table 4).

As for the general total volume models, Model DT2 and WT2 were found to be the best among models with dbh only in both sites Degaga–Gambo (pseudo- $R^2=0.99$, RMSE=19.3%) and Wondo Genet (pseudo- $R^2=0.91$, RMSE=51.4%) respectively. Inclusion of ht into the models improved performance marginally for Degaga–Gambo, but not for Wondo Genet. All the models for Degaga–Gambo performed better than the corresponding models in Wondo Genet. We also tested the general Model GT2 on the specific data from the two sites, but MPE was not significantly different from zero for any of them.

Table 5 shows the results when testing the use of form factor approach and the previously developed models to predict total volume for our data. With $f_{0.5}$, total volume is significantly ($p > 0.05$) underpredicted (16.1%), while when applying f_{mean} (0.64), volume tended to be overpredicted, although not significantly. Generally, the previously developed models over- or underpredict volume, although the difference between observed and predicted volume is not significantly different from zero when applying the models developed by Mauya et al. (2014) and Mugasha et al.

Table 4 Model parameters and performance indicators for site-specific total volume models

Site	Model	Parameters			Pseudo- R^2	RMSE		MPE		AIC
		<i>a</i>	<i>b</i>	<i>c</i>		(m ³)	(%)	(m ³)	(%)	
Degaga–Gambo (<i>n</i> =32)	DT1	−0.1517000 ²	0.0013560		0.97	0.897	31.0	−0.0002	−0.1	70
	DT2	0.0001306	2.5280000		0.99	0.558	19.3	−0.0003	−0.0	51
	DT3	0.0000411 ²	1.0080000		0.99	0.587	20.3	−0.0001	−0.0	51
	DT4	0.0000744	2.1840000	0.6144000²	0.99	0.519	17.9	0.0001	0.0	46
Wondo Genet (<i>n</i> =31)	WT1	−0.1866000 ¹	0.0014720		0.90	1.773	54.7	−0.0011	−0.0	115
	WT2	0.0001190	2.5650000		0.91	1.665	51.4	0.0005	0.0	112
	WT3	0.0000608²	0.9811000		0.91	1.680	51.8	0.0042	0.1	115
	WT4	0.0000880 ²	2.5520000	0.1071000*	0.89	1.846	57.0	0.0027	0.1	113

Best performed models shown in bold

*Non-significant parameter ($p > 0.05$); ¹ $p < 0.05$; ² $p < 0.01$; all other parameters $p < 0.001$

Table 5 Testing the use of form factor and previously developed models for predicting total tree volume from our data

Model type	Predicted volume (m ³)	RMSE		MPE	
		(m ³)	(%)	(m ³)	(%)
$f_{0.5}$	2.574	1.423	46.4	0.493**	16.1
f_{mean} (0.64)	3.296	1.169	38.1	−0.229	−7.5
Mauya et al. (2014): dbh only	2.727	1.264	41.2	0.339*	11.1
Kachamba and Eid (2016): dbh only	2.675	1.655	54.0	0.391	12.8
Mugasha et al. (2016): dbh only	2.318	2.214	72.2	0.749**	24.4
Mauya et al. (2014): dbh and ht	3.081	1.020	33.3	−0.015	−0.5
Kachamba and Eid (2016): dbh and ht	4.103	1.957	63.8	−1.036***	−33.8
Mugasha et al. (2016): dbh and ht	2.870	1.073	35.0	0.196	6.4
Current study (GT2)	3.030	1.021	33.3	0.006	0.2

n = 63; observed total volume is 3.066 m³

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(2016) with both dbh and ht as independent variables. Figure 2 illustrates how all the models developed by Mauya et al. (2014), Kachamba and Eid (2016) and Mugasha et al. (2016), using only dbh as independent variable underpredicted volume consistently for medium and larger dbh sizes as compared to the corresponding model developed in the present study (Model GT2, Table 3).

Volume-weighted wbd values for 30 different tree species are documented in Table 6. The species-wise overall volume-weighted mean ($n = 30$ species) wbd was 0.588 g cm^{-3} and ranged between 0.426 and 0.979 g cm^{-3} . At individual tree level ($n = 63$), the overall volume-weighted mean wbd was 0.553 g cm^{-3} and ranged between 0.380 and 0.979 g cm^{-3} . Among the species, *T. nobilis*, *D. angustifolia* and *O. capensis* were found to be the top three with the largest wbd values of 0.979 , 0.816 , and 0.779 g cm^{-3} , respectively; while *A. falcatus*, *P. viridiflorum* and *V. amygdalina* were the three species with the smallest wbd values with 0.426 , 0.441 and 0.457 g cm^{-3} , respectively.

Analysis of variance revealed that wbd values were significantly different ($p < 0.001$) among the tree species, while they were not significantly different ($p > 0.05$) between sites. In addition, analyses showed that there were no significant differences in wbd among the three samples collected from the stem sections (at breast height, at midpoint and at upper part) or among the three branch sizes (small, medium and large branches). The species-wise overall mean wbd for samples from stem, branch, and breast height position were also determined, and found to be 0.590 , 0.589 and 0.576 g cm^{-3} , respectively (Table 8 in Appendix); and analyses of variance

revealed no significant differences between these means ($p > 0.05$).

The outputs from regression analysis of wbd against variables describing growing conditions revealed non-significant parameter estimates for all the tested variables (Table 7) and a very small value of coefficient of determination. Still, when considering the signs of the parameter estimates, wbd was negatively influenced by elevation and basal area but positively influenced by slope. Concerning aspect, trees facing to the south tend to have higher wbd than the trees facing north.

Discussion

Models for tree biometric properties

The present study reported multi-species ht–dbh, dbh–dsh and bt–dbh models (Table 2), based on 1345 trees and 60 tree species, representing the study of dry Afromontane forests. Our ht–dbh model explained about 72% of the variation in ht, which is similar to models developed for four different natural forest types in Tanzania (Mugasha et al. 2013). Tree height measurement is challenging and susceptible to errors in tropical forests with complex tree architecture. Thus, the presence of local ht–dbh models may play a considerable role in reducing measurement errors (Larjavaara and Muller-Landau 2013; Mugasha et al. 2019).

The dbh–dsh model explained 98% of the variance. Similarly, other studies have reported strong dbh–dsh relationship

Fig. 2 Relationship of tree diameter against predicted total volume of selected previous models and the current study (Model GT2). Vertical lines indicate the maximum dbh used in the studies by Mauya et al. (2014), the current study, and Kachamba and Eid (2016), respectively

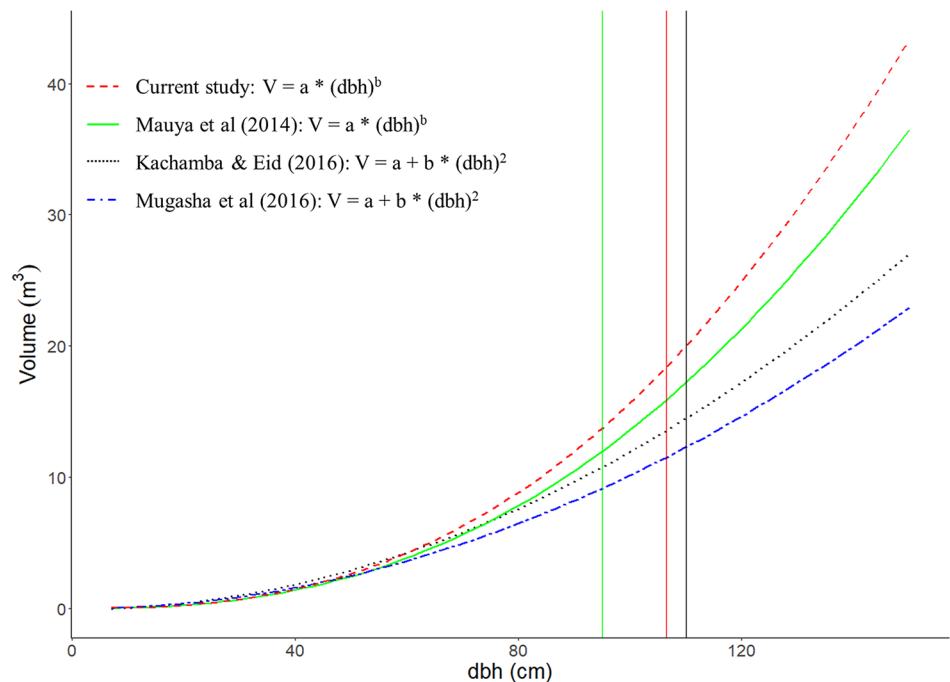


Table 6 Mean and range of volume-weighted wbd values by tree species

Scientific name	No. of sample trees	wbd (g cm ⁻³)	
		Mean	Range
<i>Acokanthera schimperi</i> (A. DC.) Schweinf.	1	0.621	
<i>Afrocarpus falcatus</i> (Thumb.) Mirb.	9	0.426	0.401–0.480
<i>Albizia gummifera</i> (J.F.Gmel.) C. A. Sm.	3	0.534	0.499–0.598
<i>Allophylus abyssinicus</i> Radlk.	2	0.509	0.509–0.515
<i>Apodytes dimidiata</i> E. Mey ex Am.	1	0.556	
<i>Bersama abyssinica</i> Fresen.	1	0.576	
<i>Canthium oligocarpum</i> Hiern	1	0.473	
<i>Cassipourea malosana</i> Alston	2	0.663	0.605–0.683
<i>Celtis africana</i> Burm. F.	5	0.631	0.615–0.658
<i>Combretum molle</i> R. Br. ex. G. Don	1	0.701	
<i>Croton macrostachyus</i> Hochst. ex. Delile.	5	0.511	0.430–0.521
<i>Dodonaea angustifolia</i> L. f.	1	0.816	
<i>Ekebergia capensis</i> Sparm.	1	0.532	
<i>Ficus thonningii</i> Blume	1	0.471	
<i>Galiniera coffeoides</i> Delile	1	0.563	
<i>Maesa lanceolata</i> Forssk.	3	0.483	0.457–0.536
<i>Maytenus arbutifolia</i> (Hochst. ex. A. Rich) R. Wilczek	2	0.615	0.615–0.622
<i>Millettia ferruginea</i> Hochst	4	0.550	0.380–0.554
<i>Nuxia congesta</i> R. Br.	2	0.537	0.498–0.603
<i>Olea capensis</i> L.	1	0.779	
<i>Olea welwitschii</i> (Knohl.) Gilg. & Schellenb.	1	0.700	
<i>Olinia rochetiana</i> A. Juss.	1	0.544	
<i>Osyris quadripartita</i> Salzam. ex Decne.	1	0.690	
<i>Pittosporum viridiflorum</i> Sims	1	0.441	
<i>Pouteria adolfi-friedericii</i> (Engl.) Baehni	4	0.460	0.458–0.567
<i>Prunus africana</i> (Hook.f.) Kalkman	3	0.609	0.608–0.615
<i>Syzygium guineense</i> (Willd.) DC.	2	0.580	0.579–0.590
<i>Teclea nobilis</i> Delile	1	0.979	
<i>Vepris dainellii</i> (Pic. Serm.) Kokwaro	1	0.631	
<i>Vernonia amygdalina</i> Del	1	0.457	

(Corral-Rivas et al. 2007; Özçelik et al. 2010). This indicates that the model is important for volume or biomass quantification, particularly where there is only dsh data. More importantly, the model is helpful to estimate the magnitude of forest degradation and carbon loss from remaining stumps, which is presently a challenge in REDD + MRV practices (UN-REDD 2017).

Table 7 Parameter estimates and *p* values from linear regression analysis of wbd as a dependent variable and some growing factors as independent variables

	Parameters	<i>p</i> value
Intercept	0.762300	< 0.0000
Elevation (m)	–0.000103	0.1950
Slope (%)	0.000317	0.7960
Basal area (m ² ha ⁻¹)	–0.000262	0.9030
Aspect (south)	0.009509	0.7730

The bt–dbh model explained only 42% of the variation in bt. The model has a larger RMSE (49%) than some similar previously developed models, e.g. by Zeibig-Kichas et al. (2016) in the USA (RMSE of about 25%), but the MPE was not significantly different from zero, indicating that the model has an appropriate behaviour. Although some uncertainty will be involved in application due to the large RMSE, the model can be used for predicting bt at breast height, which may be useful in itself. Based on the bt predicted from the model, it is also possible indirectly to quantify tree properties relevant to forest management, such as volume of solid wood and volume of bark (van Laar and Akça 2007; Kershaw et al. 2017).

Tree and forest volume may be used for planning and monitoring of forest management practices (West 2009). Merchantable stem volume is needed to evaluate trees from a timber production perspective, but may also be useful when determining compensations for timber loss due to several

reasons such as road construction (Melemez 2012). Branch volume estimates, particularly for big trees that have been used for timber production, maybe useful to estimate fuelwood quantities. Thus, our models remain crucial for the aspired sustainable utilization of the natural forests in Ethiopia (Ayele et al. 2018).

Generally, the total tree volume models explained about 93–95% of the variation in volume (Table 3). Model GT2, with dbh only as independent variable performed better than the other models, i.e. Model GT3 with dbh and ht as independent variables revealed a marginally larger RMSE than Model GT2. The same applies to the merchantable stem volume models, i.e. Model GMS2 with dbh only and Model GMS4 with both dbh and ht, where the differences in RMSE again were marginal. The fact that inclusion of ht in the models revealed none or marginal improvements, conforms with studies in natural forest elsewhere in eastern Africa (e.g. Mauya et al. 2014; Mugasha et al. 2016). The branch volume models generally exhibited poorer performance than the total and merchantable stem volume models. Among the six branch volume models, Model GB2 with dbh and Model GB6 with dbh and crw had significant model parameters and the smallest MPE with pseudo- R^2 of 0.74 and 0.89, respectively. The relatively poor performance of the branch volume models might be attributed to the different branching habits of the different species. Similar findings regarding poor performance of branch volume models are also previously reported (Mauya et al. 2014; Kachamba and Eid 2016).

We also developed site-specific total volume models for Degaga–Gambo and Wondo Genet (Table 4). Site-specific models usually provide more accurate site-specific results than general models developed with data from multiple sites (Penman et al. 2003). Accordingly, we recommend the site-specific models to be applied for their respective sites. Furthermore, we recommend to use Models DT2 and DT4 for Degaga–Gambo and Models WT2 and WT3 for Wondo Genet with dbh only and with dbh and ht entries, respectively, depending on the availability of data.

No previous volume models have been developed in Ethiopia, neither for dry Afromontane forests in particular, nor in general for natural forests. When applying the most relevant volume models from elsewhere in eastern Africa (Mauya et al. 2014; Kachamba and Eid 2016; Mugasha et al. 2016) on our data, the results showed that the MPEs in many cases were quite large (Table 5; Fig. 2). This is not surprising since these models were applied outside the ecological range they are developed for. Form factor $f_{0.5}$, along with dbh and ht, is often used in Ethiopia to determine tree volume (e.g. Sisay et al. 2017). Our result on the use of $f_{0.5}$ and f_{mean} showed that both form factors produced large MPEs, although the use of f_{mean} performed relatively better (Table 5). A study in Tanzania (Masota et al. 2014) conforms with our results, while a study in India (Adekunle et al. 2013) found volume

estimates using mean form factors similar to estimates using volume models. However, in our case, the use of form factors should be avoided since the models provide much better results.

Since no other appropriate options exist, we recommend the general models developed in this study also to be applied for dry Afromontane forests elsewhere in the country. The fact that the test of the general Model GT2 on data from the two specific sites did not reveal significant MPEs for any of the sites, is also indicating that this could be a viable option. Still, however, it is important to carefully evaluate species composition, and growing conditions related to altitude, rainfall, temperature and edaphic factors before utilizing our models. We also recommend applying Models GT2, GMS2 and GB2, based on only dbh as independent variable, in volume predictions for total, merchantable stem and branch, respectively. This will provide reasonably accurate predictions, and since these models do not require ht data, the inventory costs will be reduced. However, it is important to note that for branch volume, more accurate predictions can be made using Model GB6 if crw data are available besides dbh.

Wood basic density data

The wbd data of this study (Table 6) together with data from other studies (e.g. Ubuy et al. 2018a; Tesfaye et al. 2019) will help to develop a national wbd database for Ethiopia. Wood basic density data for 420 tree species have previously been compiled in Ethiopia's FRL report (UN-REDD 2017), but only a few of the wbd values were based on data from Ethiopia. The remaining was obtained mainly from the GWD database. In addition, the locally determined wbd values in the national database were determined at air dry basis (Desalegn et al. 2012), which means that some distortion may occur when converting them into oven dry basis (Vieilledent et al. 2018). Among the locally determined wbd values in the national database, we noted that for the 12 species also found in our study sites, they all had larger values as compared to our values. We have also recognized that 11 of the species in our list were not included in the GWD database (Chave et al. 2009; Zanne et al. 2009). Since our procedure in wbd determination is congruent with the requirement stated by Chave et al. (2006) and Williamson and Wiemann (2010), there is a possibility to incorporate the new Ethiopian wbd values into the GWD database.

The wbd values in our study varied significantly among species. The same was reported in some previous studies in Ethiopia (Ubuy et al. 2018a; Tesfaye et al. 2019). It is so because all species have inherent genetic makeup that governs its characteristics (Chave et al. 2006). Interestingly, there was no significant difference between our two sites in terms of mean wbd; perhaps due to the fact that they both

belong to the same forest type. This is in fact a good indication that the wbd values also can be applied elsewhere in a similar forest type. This can be further consolidated by comparing wbd of two species *A. abyssinicus* (0.510 g cm^{-3}) and *O. rochetiana* (0.560 g cm^{-3}) from Tesfaye et al. (2019), a study conducted in a dry Afromontane forest of central Ethiopia, with our findings that happened to be quite similar (i.e. 0.509 and 0.544 g cm^{-3} , respectively). On the other hand, when comparing the wbd of seven common species from Ubuy et al. (2018a), the values were generally larger than ours and the differences ranged from 0.001 to 0.218 g cm^{-3} . Although some studies (e.g. Chave et al. 2009; Tesfaye et al. 2019) stated that wbd varies along the stem, we did not find any significant wbd differences along the stems, or among different branch sizes. Similarly, the overall stem and branch wbd values were not significantly different. This finding was contrary to some studies (e.g. Okai et al. 2003), while being in agreement with others (e.g. Swenson and Enquist 2008).

Many previous studies have found that wbd is influenced by growing conditions (e.g. Muller-Landau 2004; Ubuy et al. 2018a). In our study, no significant parameter estimates were found when we tested a few variables describing growing conditions by means of regression analysis (Table 7). Still, the signs of the parameter estimates might provide an indication of the effects. Elevation, for example, influenced wbd negatively. This confirms our hypothesis that both precipitation and growth will increase with elevation, and accordingly wbd will be smaller. Such a result is also in agreement with previous findings (Chave et al. 2006). Similarly, the effect of slope confirms our hypothesis, because increasing slope inclination might be associated with moisture stress, as water drains quickly, leading to slow growth and higher wbd. A similar finding was reported by Barij et al. (2007). Furthermore, we hypothesized that as basal area increases, the competition among trees becomes more intense, leading to slower growth and higher wbd. The results from the analyses, however, showed an opposite effect. Similarly, the result derived from the effect of aspect was the opposite of our hypothesis since trees on south facing slopes tended to have higher wbd than trees on north facing slopes. This could be due to more moisture stress due to higher evapotranspiration caused by longer exposure to sunlight for south facing slopes, implying slow growth, but denser wood. The work by Diaconu et al. (2016) also showed that south-west facing trees tend to have larger wbd.

Conclusions

This study provided the first comprehensive biometric datasets and models that can be used when working towards sustainable forest management including REDD + MRV practices in the dry Afromontane forests of south-central Ethiopia. Applying the ht–dbh model may have dual advantages of

obtaining accurate ht estimates and of reducing costs in ht measurements while the dbh–dsh model may significantly contribute to estimation of biomass loss from forest degradation. The volume models are the first ones developed based on destructive sampling for natural forests in Ethiopia and facilitate a significant step forward for the management. The models may also be applied to dry Afromontane forest areas outside the present study sites. It is, however, important to carefully evaluate the growing conditions in such areas before model application. The documented wbd data were based on a robust sampling scheme that represented the whole tree. The absence of significant differences between the two sites in terms of wbd and comparisons with findings from other studies indicate that the wbd data are applicable to other dry Afromontane forests as well. The wbd data from the present study will be useful for building up a national wbd database and may potentially also be included in the GWD database.

Author contribution statement ZA, TE and TG designed the study. ZA performed data collection, laboratory work, data analysis and wrote the manuscript. MN supervised the data collection. TE provided additional input to analyses and interpretation of the results; contributed to the writing of the manuscript. TG and MN commented on and edited the manuscript.

Acknowledgements Open Access funding provided by Norwegian University of Life Sciences. This work was done as part of the project “National MRV capacity building towards climate resilient development in Ethiopia” hosted by Wondo Genet College of Forestry and Natural Resources, Hawassa University (WGCFNR-HU) and financially supported by the Norwegian government through the Royal Norwegian Embassy Addis Ababa Ethiopia. Many thanks go to the Norwegian University of Life Sciences, Faculty of Environmental Science and Natural Resource Management. Special thanks should also go to the Oromia Forest and Wildlife Enterprise and WGCFNR-HU, Ethiopia for the permissions to carry out the destructive sampling work. We would like also to extend our gratitude to all individuals and institutions those who supported us one way or the other during field and laboratory works.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

Appendix

See Fig. 3, Table 8.

Fig. 3 Scatter plot of total volume against dbh (left) and ht (right) panel for both study sites, Degaga–Gambo and Wondo Genet (from top to bottom)

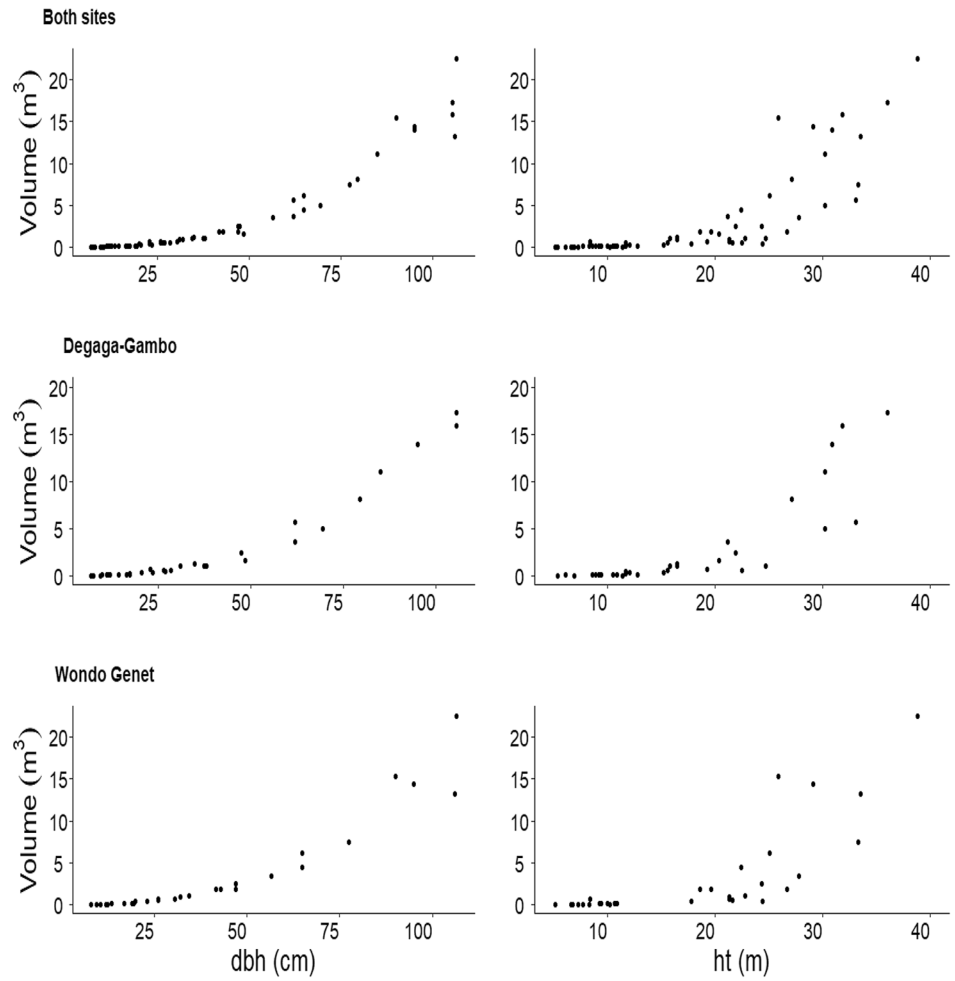


Table 8 Mean and range for dbh (cm), ht (m), crw (m) and wbd (g cm⁻³) of stem, branch and at breast height position by species

Scientific name	Local name ^a	n	dbh (cm)		ht (m)		crw (m)		Stem wbd		Branch wbd		Breast height wbd	
			Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range
<i>Acokanthera schimperi</i>	Qeraru (S)	1	17.0		9.4		5.9		0.756		0.481		0.602	
<i>Afrocarpus falcatus</i>	Birbira (O)	9	47.2	9.5–105.5	19.7	6.9–36.0	9.6	3.4–17.7	0.419	0.373–0.451	0.504	0.383–0.610	0.425	0.348–0.513
<i>Albizia gummifera</i>	Sesa (A)	3	87.2	65.0–106.5	29.9	25.1–38.8	20.3	16.1–23.9	0.522	0.474–0.611	0.548	0.525–0.582	0.552	0.413–0.795
<i>Allophylus abyssinicus</i>	Hirqamuu (O)	2	36.3	10.5–62	14.0	6.8–21.2	8.5	4.5–12.5	0.505	0.489–0.522	0.503	0.466–0.540	0.467	0.465–0.469
<i>Apodytes dimidiata</i>	Arabdotteesaa (O)	1	37.5		24.7		6.1		0.548		0.596		0.540	
<i>Bersama abyssinica</i>	Koraqaa (O)	1	27.0		11.7		6.7		0.577		0.575		0.563	
<i>Canthium oligocarpum</i>	Amshiqqaa (O)	1	28.5		15.6		5.7		0.463		0.499		0.440	
<i>Cassipourea malosana</i>	Xiillo (O)	2	10.0	8.0–12.0	8.0	6.6–9.4	5.1	4.9–5.4	0.618	0.551–0.684	0.724	0.680–0.768	0.669	0.660–0.677
<i>Celtis africana</i>	Amalaqa (O)	5	49.2	20.0–95.0	24.6	21.3–29.1	10.4	8.1–16.3	0.635	0.614–0.656	0.622	0.561–0.663	0.604	0.502–0.681
<i>Combretum molle</i>	Abalo (A)	1	12.0		7.7		3.6		0.701		0.702		0.784	
<i>Croton macrostachyus</i>	Mokkomisa (O)	5	43.6	11.5–85.0	22.1	10.5–30.2	11.3	3.6–20.0	0.479	0.426–0.511	0.521	0.468–0.561	0.482	0.436–0.565
<i>Dodonaea angustifolia</i>	Kitkita (A)	1	13.5		9.3		6.8		0.776		0.869		0.780	
<i>Ekebergia capensis</i>	Ononu (O)	1	62.0		33.1		12.9		0.521		0.554		0.530	
<i>Ficus thonningii</i>	Dimbicho (S)	1	47.0		18.6		8.2		0.472		0.469		0.428	
<i>Galiniera coffeoides</i>	Korallaa (O)	1	11.3		8.6		4.1		0.572		0.545		0.535	
<i>Maesa lanceolata</i>	Abbayyi (O)	3	23.3	14.5–38.0	12.0	9.2–15.8	5.0	3.5–6.8	0.489	0.455–0.538	0.492	0.460–0.532	0.477	0.430–0.520
<i>Maytenus arbustifolia</i>	Kombolcha (O)	2	12.3	7.0–17.5	8.6	5.4–11.7	4.2	3.4–4.9	0.629	0.628–0.630	0.581	0.580–0.583	0.672	0.668–0.675
<i>Milletia ferruginea</i>	Dhaadhaatu (O)	4	47.4	8.0–77.5	24.1	10.2–33.3	8.9	2.4–13.1	0.496	0.378–0.551	0.520	0.470–0.574	0.526	0.487–0.580
<i>Nixta congesta</i>	Bixxannaa (O)	2	21.3	19.0–23.5	11.1	10.0–12.1	4.7	4.3–5.0	0.552	0.505–0.599	0.549	0.490–0.608	0.558	0.526–0.590
<i>Olea capensis</i>	Sigeda (O)	1	23.0		19.3		7.1		0.788		0.771		0.794	
<i>Olea welwitschii</i>	Wolincho (S)	1	19.5		10.9		5.9		0.724		0.678		0.635	
<i>Olinia rochetiana</i>	Gunaa (O)	1	7.5		11.4		2.4		0.546		0.498		0.602	
<i>Osyris quadripartita</i>	Kaaro (O)	1	30.5		8.4		7.8		0.724		0.660		0.749	
<i>Pittosporum viridiflorum</i>	Aaraa (O)	1	10.5		5.2		3.8		0.432		0.480		0.440	
<i>Pouteria adolfi-friedericii</i>	Sudubaa (O)	4	42.1	13.5–106.0	20.9	10.7–33.5	7.6	3.7–15.9	0.501	0.454–0.593	0.406	0.329–0.474	0.478	0.430–0.530
<i>Prunus africana</i>	Sukkee (O)	3	53.3	11.5–105.5	21.4	12.8–31.9	8.4	5.3–13.3	0.603	0.599–0.606	0.652	0.613–0.688	0.603	0.593–0.621
<i>Syzygium guineense</i>	Baddeessa (O)	2	53.0	26.5–79.5	24.8	22.5–27.1	10.7	6.9–14.6	0.585	0.584–0.586	0.584	0.569–0.599	0.532	0.516–0.549
<i>Teclea nobilis</i>	Hadhesaa (O)	1	9.5		7.3		5.2		0.962		0.994		0.763	
<i>Vepris dainellii</i>	Lela (S)	1	12.5		8.3		5.7		0.619		0.645		0.584	
<i>Vernonia amygdalina</i>	Ebicha (O)	1	10.0		6.1		2.9		0.471		0.433		0.473	

^aLocal name (A): in Amharic, (O): in Oromifa, and (S): in Sidaamu Afoo; n no. of sample trees

References

- Adekunle VAJ, Nair KN, Srivastava AK, Singh NK (2013) Models and form factors for stand volume estimation in natural forest ecosystems: a case study of Katarniaghat wildlife sanctuary (KGWS), Bahraich District, India. *J For Res* 24:217–226. <https://doi.org/10.1007/s11676-013-0347-8>
- Ayele G, Mezmur S, Hussien S (2018) Guideline for sustainable timber harvesting in participatory forest management forests. Farm Africa, Addis Ababa
- Barij N, Stokes A, Bogaard T, Van Beek R (2007) Does growing on a slope affect tree xylem structure and water relations? *Tree Physiol* 27:757–764. <https://doi.org/10.1093/treephys/27.5.757>
- Baty F, Ritz C, Charles S, Brutsche M, Flandrois JP, Delignette-Muller ML (2015) A toolbox for nonlinear regression in R: the package nlstools. *J Stat Softw* 66(5):1–21. <https://www.jstatsoft.org/v66/i05/>
- Berhe L (2009) Volume and implicit taper functions for *Cupressus lusitanica* and *Pinus patula* tree plantations in Ethiopia. *Ethioph J Environ Stud Manag* 2:12–28. <https://doi.org/10.4314/ejesm.v2i1.43498>
- Bollandsås OM, Zahabu E, Katani JZ (2016) Background on the development of biomass and volume models. In: Malimbwi RE, Eid T, Chamshama SAO (eds) Allometric tree biomass and volume models in Tanzania. Department of forest mensuration and management Sokoine University of Agriculture, Morogoro, pp 9–18
- Chave J, Muller-Landau HC, Baker TR, Easdale TA, Steege HT, Webb CO (2006) Regional and phylogenetic variation of wood density across 2456 neotropical tree species. *Ecol Appl* 16:2356–2367. [https://doi.org/10.1890/1051-0761\(2006\)016\[2356:RAPVO W\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2006)016[2356:RAPVO W]2.0.CO;2)
- Chave J, Coomes D, Jansen S, Lewis SL, Swenson NG, Zanne AE (2009) Towards a worldwide wood economics spectrum. *Ecol Lett* 12:351–366. <https://doi.org/10.1111/j.1461-0248.2009.01285.x>
- Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WB, Duque A, Eid T, Fearnside PM, Goodman RC, Henry M, Martínez-Yrizar A, Mugasha WA, Muller-Landau HC, Mencuccini M, Nelson BW, Ngomanda A, Nogueira EM, Ortiz-Malavassi E, Péllissier R, Ploton P, Ryan CM, Saldarriaga JG, Vieilledent G (2014) Improved allometric models to estimate the above ground biomass of tropical forests. *Glob Change Biol* 20:3177–3190. <https://doi.org/10.1111/gcb.12629>
- Corral-Rivas JJ, Barrio-Anta M, Aguirre-Calderon OA, Dieguez-Aranda U (2007) Use of stump diameter to estimate diameter at breast height and tree volume for major pine species in El Salto, Durango (Mexico). *Forestry* 80:29–40. <https://doi.org/10.1093/forestry/cpl048>
- Desalegn G, Abegaz M, Teketay D, Gezahgne A (2012) Commercial timber species in Ethiopia: characteristics and uses. A handbook for forest industries, construction and energy sectors, foresters and other stakeholders. Addis Ababa University Press, Addis Ababa. <https://publication.eiar.gov.et:8080/xmlui/handle/123456789/2920>. Accessed Aug 2019
- Diaconu D, Wassenberg M, Spiecker H (2016) Variability of European beech wood density as influenced by interactions between tree-ring growth and aspect. *For Ecosyst* 3:6. <https://doi.org/10.1186/s40663-016-0065-8>
- Erikson H, Stern M (1987) A soil study at Wondo Genet Forestry Resource Institute, Ethiopia. Swedish University of Agricultural Science, International Rural Development Centre, Uppsala
- Eriksson I, Teketay D, Granstrom (2002) Response of plant communities to fire in an *Acacia* woodland and dry Afromontane forest, southern Ethiopia. *For Ecol Manag* 177:39–50. [https://doi.org/10.1016/S0378-1127\(02\)00325-0](https://doi.org/10.1016/S0378-1127(02)00325-0)
- Feldpausch T, Banin L, Phillips O, Baker T, Lewis S, Quesada C, Affum-Baffoe K, Arets E, Berry N, Bird M et al (2011) Height–diameter allometry of tropical forest trees. *Biogeosciences* 8:1081–1106. <https://doi.org/10.5194/bg-8-1081-2011>
- Friis I, Demissew S, Breugel PV (2010) Atlas of the potential vegetation of Ethiopia. Det Kongelige Danske Videnskabernes Selskab, Copenhagen
- Fritzsche F, Zech W, Guggenberger G (2007) Soils of the main Ethiopian Rift Valley escarpment: a transect study. *CATENA* 70:209–219. <https://doi.org/10.1016/j.catena.2006.09.005>
- Githiomi JK, Kariuki JG (2010) Wood basic density of *Eucalyptus grandis* from plantations in Central Rift Valley, Kenya: variation with age, height level and between sapwood and heartwood. *J Trop For Sci* 22:281–286. <https://www.jstor.org/stable/23616657>
- Guillozet K, Bliss JC, Kelecha TS (2014) Degradation in an Afromontane forest in highland Ethiopia, 1969–2010. *Small Scale For* 14:121–137. <https://doi.org/10.1007/s11842-014-9277-3>
- Henry M, Besnard A, Asante WA, Eshun J, Adu-Bredu S, Valentini R, Bernoux M, Saint-André L (2010) Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. *For Ecol Manag* 260:1375–1388. <https://doi.org/10.1016/j.foreco.2010.07.040>
- Henry M, Picard N, Trotta C, Manlay RJ, Valentini R, Bernoux M, Saint-André L (2011) Estimating tree biomass of sub-Saharan African forests: a review of available allometric equations. *Silva Fenn* 45:477–569. <https://doi.org/10.14214/sf.38>
- James G, Witten D, Hastie T, Tibshirani R (2013) An introduction to statistical learning: with applications in R. Springer, New York
- Kachamba D, Eid T (2016) Total tree, merchantable stem and branch volume models for miombo woodlands of Malawi. *South For J For Sci* 78:41–51. <https://doi.org/10.2989/20702620.2015.1108615>
- Kebede M, Kanninen M, Yirdaw E, Lemenih M (2013) Vegetation structure characteristics and topographic factors in the remnant moist Afromontane forest of Wondo Genet, south central Ethiopia. *J For Res* 24:419–430. <https://doi.org/10.1007/s11676-013-0374-5>
- Kershaw JA, Ducey MJ, Beers TW, Husch B (2017) Forest mensuration, 5th edn. Wiley, Chichester, Hoboken
- Kelly JF, Beltz RC (1987) A comparison of tree volume estimation models for forest inventory. Research paper SO-233, USDA forest serve, Southern forest experiment station. New Orleans, Louisiana. <https://doi.org/10.2737/SO-RP-233>
- Larjavaara M, Muller-Landau HC (2013) Measuring tree height: quantitative comparison of two common field methods in a moist tropical forest. *Method Ecol Evol* 4:793–801. <https://doi.org/10.1111/2041-210X.12071>
- Lemenih M, Kassa H (2014) Re-greening Ethiopia: history, challenges and lessons. *Forests* 5:1896–1909. <https://doi.org/10.3390/f5081896>
- Lemenih M, Allan C, Biot Y (2015) Making forest conservation benefit local communities: participatory forest management in Ethiopia. Farm Africa. <https://www.farmafrica.org/downloads/resources/pfmfinalweb.pdf>. Accessed Aug 2019
- Lindner M, Karjalainen T (2007) Carbon inventory methods and carbon mitigation potentials of forests in Europe: a short review of recent progress. *Eur J For Res* 126:149–156. <https://doi.org/10.1007/s10342-006-0161-3>
- Masota AM, Zahabu E, Malimbwi RE, Bollandsås OM, Eid TH (2014) Volume models for single trees in tropical rainforests in Tanzania. *J Energy Nat Resour* 3:66–76. <https://doi.org/10.11648/j.jenr.20140305.12>
- Mauya EW, Mugasha WA, Zahabu E, Bollandsås OM, Eid T (2014) Models for estimation of tree volume in the miombo woodlands of Tanzania. *South For J For Sci* 76:209–219. <https://doi.org/10.2989/20702620.2014.957594>
- MEFCC (2018) National Forest Sector Development Program, Ethiopia. Volume I: situation analysis. Ministry of Environment Forest and Climate Change. <https://www.et.undp.org/content/ethiopia/en/>

- [home/library/ten-year-national-forest-sector-development-programme.html](#). Accessed Aug 2019
- Melemez K (2012) An environmental assessment of forest stands damages caused by excavators during road construction in Beech forests. *Int J Environ Sci Technol* 10:645–650. <https://doi.org/10.1007/s13762-012-0125-8>
- Missanjo E, Matsumura J (2016) Wood density and mechanical properties of *Pinus kesiya* Royle ex Gordon in Malawi. *Forests* 7:7–35. <https://doi.org/10.3390/f7070135>
- Mittermeier RA, Robles Gil P, Hoffman M, Pilgrim J, Brooks T (2004) Hotspots revisited: Earth's biologically richest and most endangered terrestrial ecoregions. University of Chicago Press, Chicago
- Mokria M, Gebrekirstos A, Aynekulu E, Bräuning A (2015) Tree die-back affects climate change mitigation potential of a dry afro-montane forest in northern Ethiopia. *For Ecol Manag* 344:73–83. <https://doi.org/10.1016/j.foreco.2015.02.008>
- Mokria M, Mekuria W, Gebrekirstos A, Aynekulu E, Belay B, Gashaw T, Brauning A (2018) Mixed species allometric equations and estimation of aboveground biomass and carbon stocks in restoring degraded landscape in northern Ethiopia. *Environ Res Lett*. <https://doi.org/10.1088/1748-9326/aaa495>
- Mugasha WA, Bollandsås OM, Eid T (2013) Relationships between diameter and height of trees in natural tropical forest in Tanzania. *South For J For Sci* 75(4):221–237. <https://doi.org/10.2989/20702620.2013.824672>
- Mugasha WA, Mwakalukwa EE, Luoga E, Malimbwi RE, Zahabu E, Silayo DS, Sola G (2016) Allometric models for estimating tree volume and aboveground biomass in lowland forests of Tanzania. *Int J For Res* 2016:1–13. <https://doi.org/10.1155/2016/8076271>
- Mugasha WA, Mauya EW, Njana AM, Karlsson K, Malimbwi RE, Ernest S (2019) Height–diameter allometry for tree species in Tanzania mainland. *Int J For Res*. <https://doi.org/10.1155/2019/4832849>
- Muhairwe CK (1999) Taper equation for *Eucalyptus pilularis* and *Eucalyptus grandis* for the north coast in New South Wales, Australia. *For Ecol Manag* 113:251–269. [https://doi.org/10.1016/S0378-1127\(98\)00431-9](https://doi.org/10.1016/S0378-1127(98)00431-9)
- Muller-Landau HC (2004) Interspecific and inter-site variation in wood specific gravity of tropical trees. *Biotropica* 36:20–32. <https://doi.org/10.1111/j.1744-7429.2004.tb00292.x>
- Njana MA, Meilby H, Eid T, Zahabu E, Malimbwi RG (2016) Importance of tree basic density in biomass estimation and associated uncertainties: a case of three mangrove species in Tanzania. *Ann For Sci* 73:1073–1087. <https://doi.org/10.1007/s13595-016-0583-0>
- Okai R, Frimpong-Mensah K, Yeboah D (2003) Characterization of moisture content and specific gravity of branch wood and stem wood of *Aningeria robusta* and *Terminalia ivorensis*. *Holz Roh Werkst* 61:155–158. <https://doi.org/10.1007/s00107-002-0360-7>
- Özçelik R, Brooks JR, Diamantopoulou MJ, Wiant HV (2010) Estimating breast height diameter and volume from stump diameter for three economically important species in Turkey. *Scand J For Res* 25:32–45. <https://doi.org/10.1080/02827580903280053>
- Penman J, Gytarsky M, Hiraishi T, Krug T, Kruger D, Pipatti R, Buendia L, Miwa K, Ngara T, Tanabe K, Wagner F (2003) IPCC Good Practice Guidance for land use, land-use change and forestry. <https://www.ipcc-nggip.iges.or.jp>. Accessed Aug 2019
- Pohjonen VM (1991) Volume equations and volume tables of *Juniperus procera* Hocht. ex. Endl. *J For Ecol Manag* 44:185–200. [https://doi.org/10.1016/0378-1127\(91\)90007-I](https://doi.org/10.1016/0378-1127(91)90007-I)
- Picard N, Saint-André L, Henry M (2012) Manual for building tree volume and biomass allometric equations: from field measurement to prediction. Food and Agriculture Organization of the United Nations, Rome; Centre de Coopération Internationale en Recherche Agronomique pour le Développement, Montpellier
- R Core Team (2019) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna. <https://www.R-project.org/>
- Schumacher FX, Hall FS (1933) Logarithmic expression of timber-tree volume. *J Agric Res* 47:719–734. <https://naldc.nal.usda.gov/download/IND43968352/PDF>
- Sisay K, Thurnher C, Belay B, Lindner G, Hasenauer H (2017) Volume and carbon estimates for the forest area of the Amhara region in the north-western Ethiopia. *Forests* 8(4):122. <https://doi.org/10.3390/f8040122>
- Swenson NG, Enquist BJ (2008) The relationship between stem and branch wood specific gravity and the ability of each measure to predict leaf area. *Am J Bot* 95:516–519. <https://doi.org/10.3732/ajb.95.4.516>
- Tenzin J, Wangchuk T, Hasenauer H (2016) Form factor functions for nine commercial trees in Bhutan. *Forestry* 90:359–366. <https://doi.org/10.1093/forestry/cpw044>
- Tesfaye MA, Bravo-Oviedo A, Bravo F, Pando V, de Aza CH (2019) Variation in carbon concentration and wood density for five most commonly grown native tree species in central highlands of Ethiopia: the case of Chilimo dry Afromontane forest. *J Sustain For*. <https://doi.org/10.1080/10549811.2019.1607754>
- Teshome T (2005) Analysis of individual tree volume equations for *Cupressus lusitanica* in Munessa forest, Ethiopia. *S Afr For J* 203:27–32. <https://doi.org/10.2989/10295920509505215>
- Ubuy MH, Eid T, Bollandsås OM (2018a) Variation in wood basic density within and between tree species and site conditions of exclosures in Tigray, northern Ethiopia. *Trees* 32:967–983. <https://doi.org/10.1007/s00468-018-1689-9>
- Ubuy MH, Eid T, Bollandsås OM, Birhane E (2018b) Aboveground biomass models for trees and shrubs of exclosures in the drylands of Tigray, northern Ethiopia. *J Arid Environ* 156:9–18. <https://doi.org/10.1016/j.jaridenv.2018.05.007>
- UN-REDD (2017) Ethiopia's forest reference level submission to the UNFCCC. https://redd.unfccc.int/files/ethiopia_frel_3.2_final_modified_submission.pdf. Accessed Aug 2019
- Vanclay JK (1994) Modelling forest growth and yield, application to mixed tropical forests. CAB International, Wallingford
- van Laar A, Akça A (2007) Forest mensuration. Springer, Dordrecht
- Vieilledent G, Fischer FJ, Chave J, Guibal D, Langbour P, Gérard J (2018) New formula and conversion factor to compute basic wood density of tree species using a global wood technology database. *Am J Bot*. <https://doi.org/10.1002/ajb2.1175>
- Weiskittel AR, Hann DW, Kershaw JA, Vanclay JK (2011) Forest growth and yield modelling. Wiley, Chichester
- West PW (2009) Tree and forest measurement, 2nd edn. Springer, Berlin
- Williamson GB, Wiemann MC (2010) Measuring wood specific gravity correctly. *Am J Bot* 97(3):519–524. <https://doi.org/10.3732/ajb.0900243>
- Wondrade N, Dick ØB, Tveite H (2015) Estimating above ground biomass and carbon stock in the Lake Hawassa Watershed, Ethiopia by integrating remote sensing and allometric equations. *For Res* 4:151. <https://doi.org/10.4172/2168-9776.1000151>
- Zanne AE, Lopez-Gonzalez G, Coomes DA, Ilic J, Jansen S, Lewis SL, Miller RB, Swenson NG, Wiemann MC, Chave J (2009) Data from: towards a worldwide wood economics spectrum. Dryad Digit Repos. <https://doi.org/10.5061/dryad.234>
- Zeibig-Kichas NE, Ardis CW, John-Pascal Berrill JP, King JP (2016) Bark thickness equations for mixed-conifer forest type in Klamath and Sierra Nevada mountains of California. *Int J For Res*. <https://doi.org/10.1155/2016/1864039>
- Zeng WS, Tang SZ (2011) Bias correction in logarithmic regression and comparison with weighted regression for nonlinear models. *Nat Preced*. <https://doi.org/10.1038/npre.2011.6708.1>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.