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Korotimi Ouédraogo[1], Kangbéni Dimobe[1,2,3] and Adjima Thiombiano[1]

Allometric models for estimating aboveground biomass and carbon stock for *Diospyros mespiliformis* in West Africa

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Highlights

- Biomass estimation models developed for *Diospyros mespiliformis*.
- Models based on DBH alone predicted aboveground biomass with 97.11% accuracy.
- Published models had relative error between –72% and +98%.
- Models for branch and stem biomass were more accurate than those for leaf biomass.

Abstract

Accurate estimates of aboveground biomass (AGB) strongly depend on the suitability and precision of allometric models. *Diospyros mespiliformis* Hochst. ex A. DC. is a key component of most sub-Sahara agroforestry systems and, one of the most economically important trees in Africa. Despite its importance, very few scientific information exists regarding its biomass and carbon storage potential. In this study direct method was used to develop site-specific biomass models for *D. mespiliformis* tree components in Burkina Faso. Allometric models were developed for stem, branch and leaf biomass using data from 39 tree harvested in Sudanian savannas of Burkina Faso. Diameter at breast height (DBH), tree height, crown diameter (CD) and basal diameter (D_{20}) were regressed on biomass component using non-linear models with DBH alone, and DBH in combination with height and/or CD as predictor variables. Carbon content was estimated for each tree component using the ash method. Allometric models differed between the experimental sites, except for branch biomass models. Site-specific models developed in this study exhibited good model fit and performance, with explained variance of 81–98%. Using models developed from other areas would have underestimated or overestimated biomass by between –72% and +98%. Carbon content in aboveground components of *D. mespiliformis* in Tiogo, Boulon and Tapoa-Boopo was 55.40% ± 1.50, 55.52% ± 1.06 and 55.63% ± 1.00, respectively, and did not vary significantly (P-value = 0.909). Site-specific models developed in this study are useful tool for estimating carbon stocks and can be used to accurately estimate tree components biomass in vegetation growing under similar conditions.

Keywords African ebony; biomass estimation equations; biometric variables; Burkina Faso; carbon storages; jackalberry; Sudanian savanna
Addresses [1]University Joseph Ki-Zerbo, UFR/SVT, Laboratory of Plant Biology and Ecology, 03 B.P. 7021 Ouagadougou 03, Burkina Faso; [2]University of Dédougou, Institut des Sciences de l'Environnement et du Développement Rural (ISEDR), BP 139 Dédougou, Burkina Faso; [3]West African Science Service Center on Climate Change and Adapted Land Use, Competence Center, Avenue Muamar Ghadhafi, Ouagadougou, BP 9507, Burkina Faso
E-mail okorotimi@yahoo.fr
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1 Introduction

Biomass estimates remain essential for understanding the role of forests as carbon sinks and sustainable forest management (IPCC 2006; Pan et al. 2011). Tropical forests play an important role for the climate change as a main carbon sink for the whole world. Biomass and carbon accounting in natural and semi-natural vegetation types has rapidly become the focus over the last decades (Brown 2002; Chave et al. 2005; Chauhan et al. 2010, 2012), as being paramount step towards the implementation of the emerging carbon credit market mechanism such as Reducing Emission from Deforestation and Forest Degradation (REDD+) (Bernard et al. 2014). Aboveground biomass (AGB) is a useful measure for comparing structural and functional attributes of forest and savanna ecosystems across a wide range of environmental conditions (Brown et al. 1999). AGB also serves as an indicator for the distribution and abundance of vegetation above the ground.

Tree biomass can be estimated by: (1) destructive methods (Balima et al. 2019; Dimobe et al. 2018a,b; Bayen et al. 2015), (2) Non-destructive methods (Dimobe et al. 2018c,d, 2019), and (3) remote sensing techniques (Qureshi et al. 2012; Galidaki et al. 2017). Destructive methods which involve harvesting of trees, drying and weighing different components (Brown 1997) are time consuming and costly. They are also not applicable to large areas and are restricted in protected areas or for species that are endangered compared to non-destructive methods, while remote sensing is limited by access to technology and cloud cover. Allometric biomass models are statistical formulas relating tree biometric variables (e.g. diameter at breast height, tree height, basal diameter or crown diameter) to tree dry biomass. These models can be developed by destructive sampling (Kuyah et al. 2013; Dimobe et al. 2018a,b), semi-destructive (Mensah et al. 2016, 2017) and non-destructive (MacFarlane et al. 2014; Dimobe et al. 2019), and used based on predictors such as diameter at breast height (DBH), tree height, wood density, crown diameter or basal diameter, or the combination of these variables. Although allometric models are developed by destructive sampling, once developed, they allow non-destructive estimation of biomass over a large area at relatively low cost. Allometric models for estimating AGB can be linear, logarithmic, exponential or power law (Návar 2009; Bayen et al. 2015; Mensah et al. 2016). Power law however remain the most common used model because it is supported by growth that assumes a constant scaling rate across ontogenies (Mensah et al. 2017).

A limited number of studies have developed allometric models for species in dryland environments. These are based on data derived from wider geographical range; for example Brown (1997) developed allometric models from field measurements in savanna ecosystems of South America and dry forests of India; Chave et al. (2014) reported allometric models for pantropical forests. Recent studies (Shirima et al. 2011; Kuyah et al. 2012; Chave et al. 2014; Mensah et al. 2017) have also reported allometric models specific to African ecosystems. However, few of them refer directly to Sudanian savanna ecosystems of West Africa (Sawadogo et al. 2010; Bayen et al. 2015; Dimobe et al. 2018a,b). Accurate estimates of biomass in many tropical dryland regions are still lacking because of lack of allometric models. Challenges in obtaining measured field data in these species-rich ecosystems have made it difficult to develop models for predicting biomass of individual trees (Dimobe et al. 2018a,b). This is a major constraint given that accurate estimates of biomass depend on the appropriateness of the allometric models that are used (Sileshi 2014; Picard et al. 2015). There is mounting evidence that application of models not suitable to target vegetation results in large systematic deviations from observed data.

Diospyros mespiliformis Hochst. ex A. DC. is a species of the family Ebenaceae providing important ecosystem services to local population in sub-Saharan Africa. The tree serves as wind breaks, controls soil erosion and provides a habitat for other organisms. It also has potential for climate mitigation through carbon sequestration – a function that has not been quantified. The role of *D. mespiliformis* in climate change mitigation is therefore poorly understood. Carbon storage potential of the species can be underestimated or overestimated depending on the allometric model chosen for biomass estimation. To fill this gap, we developed allometric model for prediction of aboveground biomass and the biomass of tree components for *D. mespiliformis* in Burkina Faso. The specific objectives were to (i) develop species-specific allometric models for estimating total biomass and biomass of tree components (stem, branch, leaf) using basal diameter, DBH, total height and crown diameter, (ii) compare the performance of the selected model to predict the AGB with previously published and well-established global models, and (iii) predict the carbon content in leaf, branch, stem components of *D. mespiliformis* trees.

2 Material and methods

2.1 Study area

The study was conducted in three protected areas located in the Eastern and Southwestern Regions of Burkina Faso, namely, Boulon, Tapoa-Boopo and Tiogo (Fig. 1). Description of the biophysical contexts of the three forests areas are presented in Table 1. Boulon and Tiogo forests were classified by the colonial administration in 1955 and 1940, while that of Tapoa-Boopo was classified in the 80s (FAO 2004). In terms of climate, the forest of Boulon is located in the Sudanian zone while Tapoa-Boopo and Tiogo are located in the Sudano-Sahelian zone (Guinko 1984). All three locations experience a single rain season from May to October with annual precipitation ranging

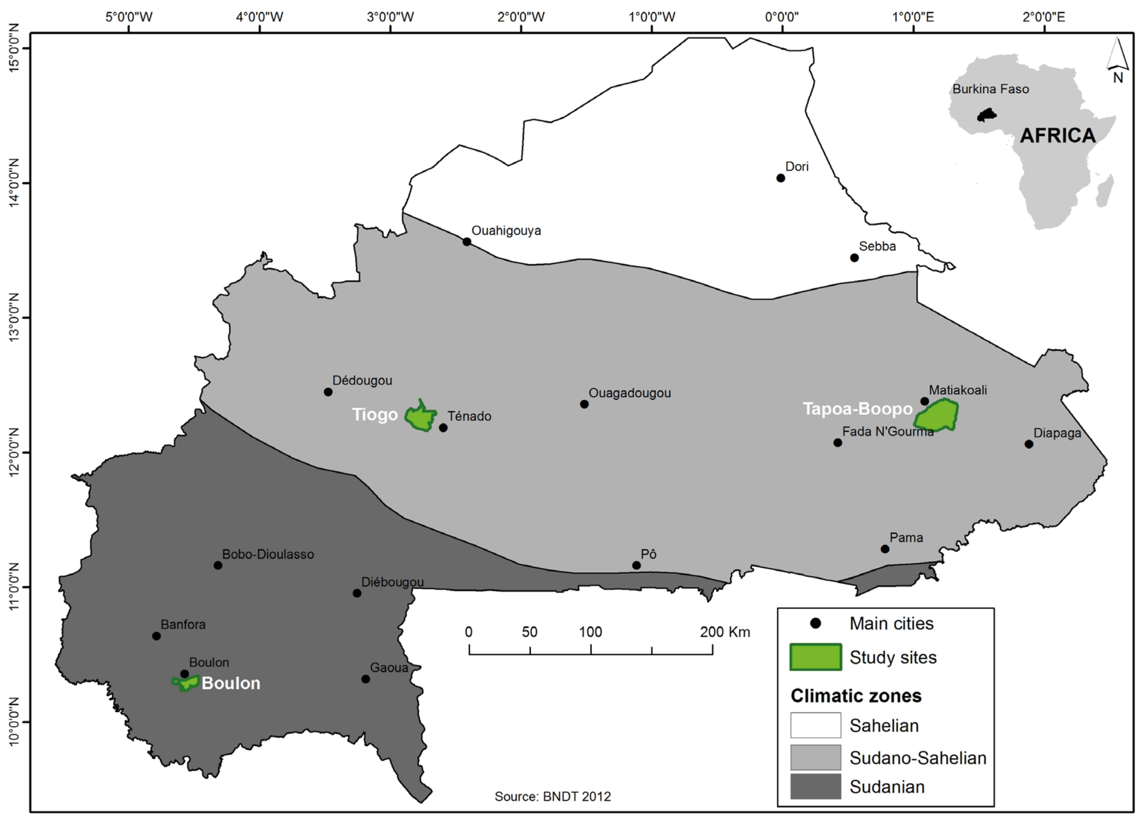

Fig. 1. Location of the study area (Bolon, Tapoa-Boopo and Tiogo forests) in Burkina Faso.

Table 1. Biophysical characteristics of Bolon, Tapoa-Boopo and Tiogo forests (Guinko 1984).

Protected areas	Boulon	Tapoa-Boopo	Tiogo
Region	Cascades	Eastern	Central-West
Location	10°15′–10°22′N; 4°20′–4°38′W	12°10′–12°23′N; 0°58′–1°13′W	12°10′–12°25′N; 2°39′–2°54′W
Area (ha)	13521.70	36202.30	30339
Climate	Sudanian	Sudano-Sahelian	Sudano-Sahelian
Annual rainfall (mm)	900–1100	600–900	600–900
Rainfall regime	Unimodal	Unimodal	Unimodal
Temperature range (°C)	17–36	25–33	25–35
Main vegetation	Dense dry forest, savannas	Tree and shrub savannas	Tree and shrub savannas

between 600–1000 mm; the rest of the year is dry. The mean annual temperature across the three sites is 35 °C; temperatures above 35 °C occur during peak period in the month of April (Bognounou 2009). Vegetation is dominated by shrub savannas, tree savannas and woodlands.

2.2 Description of the species

Diospyros mespiliformis is a mesopharenophyte that belongs to the family of Ebenaceae with a maximum height of 25 m (Arbonnier 2002). The species is widely distributed in sub-Saharan Africa, occurring from Senegal east to Eritrea, Ethiopia and Kenya, and south to Namibia, northern South Africa and Swaziland, but it is nearly absent in the more humid forest zones of West and Central Africa. It is also found in Yemen. *D. mespiliformis* is widely distributed in agroforestry parklands, woodlands, savannas and along riverbanks. Also known as African ebony or jackalberry, *D. mespiliformis* is a multipurpose species. For instance, the wood of *D. mespiliformis* is used for posts in construction, making musical instruments (e.g. drums) and household utensils (e.g. cups, spoons, pestles and mortars). The fruit are directly consumed for their vitamins and energy contents. The seeds are also eaten. The leaves are occasionally eaten as vegetable and serve as fodder for livestock. *D. mespiliformis* is commonly managed as a crop, but also grows in the wild and parklands across the sub-Saharan African savannas. It contributes ecosystem service such as wind breaks, controls soil erosion, and climate regulation.

2.3 Forest inventory and biomass sampling

Data were collected through two phases of sampling. For the first phase, forest inventory was conducted using 180 plots (60 plots for each site) of 1000 m² (50 m × 20 m) to collect data on DBH, total tree height, crown diameter and basal diameter on all individual trees of *D. mespiliformis* with DBH ≥ 5 cm inside each plot. The plots were established based on a stratified random sampling design. For the second phase, a destructive sampling of the species was carried out for quantification of tree biomass in 39 plots (13 plots for each site). Thirteen (13) individual trees of the species (one felled tree per selected plot) were harvested at each of the three sites (Boulon, Tapoa-Boopo and Tiogo), giving a total of 39 trees for measurements of biomass and subsequent development of allometric models (Table 2). To facilitate sampling, the individuals in each site were grouped into seven stem diameter classes: 10–20 (4 individual trees in Boulon, 6 in Tapoa-Boopo and 5 in Tiogo), 20–30 (5; 1 and 3), 30–40 (2; 3 and 1), 40–50 (1; 1 and 1), 50–60 (1; 0 and 2), 60–70 (0; 1 and 0) and 70–80 (0; 1 and 1). Individual trees were selected during the rainy season in June 2018 when all vegetation was in leaf. Prior to the harvesting, biometric variables, including

Table 2. Summary statistics of sample tree characteristics and biomass data.

Site	Sample trees	DBH (cm)		Height (m)		D20 (cm)		CD (m)		Aboveground tree biomass (kg)			
		Mean	Range	Mean	Range	Mean	Range	Mean	Range	Stem	Branch	Leaves	Aboveground
Boulon	13	29.6±4.6	14.6–73.5	8.5±0.7	6.0–14.9	35.8±6.3	18.1–98.5	6.8±0.8	3.7–13.6	119.7±55.4	224.1±97.7	12.7±3.7	356.6±153.1
Tapoa	13	26.1±4.4	11.5–61.5	6.6±0.5	3.5–9.2	31.9±5.6	14.5–76.1	5.7±0.8	2.9–11.9	78.2±24.6	157.9±73.9	18.2±7.1	254.3±102.0
Tiogo	13	27.58±4.5	9.4–59.5	7.1±0.8	1.7–12.0	33.2±5.4	13.5–75.5	5.9±1.1	1.9–16.1	94.4±34.2	213.8±87.5	36.2±11.6	344.4±129.1

DBH: Diameter at breast height; D20: basal diameter; CD: height and crown diameter.

DBH, total height, crown diameter and basal diameter were measured for all individual trees of *D. mespiliformis*. Crown diameter, DBH and basal diameter were measured using a diameter tape graduated in cm. Total tree height was measured from the base of the trunk to the tip of the tree using a clinometer. To avoid measurement error and to account for structural variety, the crown diameter was measured twice, along the east–west direction and the north–south one (Meyer et al. 2014). The diameter of all ramification was measured for tree forking below 1.30 m and quadratic mean diameter was computed.

Selected trees were cut at ground level using a chain saw. Felled trees were separated into stem, branches and leaves. Branches were removed from the stem and cut into weighable sections. Leaves were separated from branches and collected into bags for weighing. Fresh weights of stem, branches and leaves for each individual tree were separately determined in the field using a 100 kg scale balance. Subsamples of leaves, stem and branches were taken, and their fresh weight determined using a 5 kg electronic balance (precision 0.5 g). The subsamples of branches and stem were taken as discs of 5 cm thickness depending on the diameter of the trunk or branch. The fresh weight of each disc was recorded in the field immediately after harvesting the trees. Two hundred grams (200 g) of leaf subsample for each tree was collected into bags to facilitate weighing.

The discs and leaf samples were transported to the laboratory where they were oven dried to a constant weight at 105 °C (samples of branches and stems) or 75 °C (samples of leaves). The dry weight of the samples was recorded immediately after removal from the oven. The sample dry weight was divided by corresponding fresh weight to obtain the dry–to–green weight ratio for each tree component. Component dry weight (biomass) was computed by multiplying subsample dry–to–fresh weight ratio by the fresh weight of the respective tree component. Total aboveground biomass of the tree was calculated as the sum of the biomass of all components in kilograms.

2.4 Estimation of carbon content and carbon stocks

Carbon content in selected individuals of *Diospyros mespiliformis* was estimated using ash method (Allen et al. 1986; Jana et al. 2009; Chavan and Rasal 2011) as follows. Composite samples were obtained from the dry matter samples of leaves, branches and stems for determination of their total carbon content. The samples were crushed in a cutting mill. Five 2-g samples of each component were then collected and submitted for analysis to the Laboratory of Plants and Soils at the University Ouaga1 Joseph Ki-Zerbo (Burkina Faso). Each 2-g sample was placed in a lidless porcelain crucible and placed for 2 h inside a muffle furnace set at 550 °C, until calcination was completed. The samples were then removed and cooled in a desiccator to be weighed later. After cooling, the crucible with ash was weighed and the percentage of carbon was calculated according to the formula by Allen et al. (1986):

$$\%\text{Ash} = (W_3 - W_1)/(W_2 - W_1) \times 100 \ , \tag{1}$$

$$\%\text{Carbon} = (100\% - \%\text{Ash}) \times 0.58 \ , \tag{2}$$

where W_1 is weight of crucibles, W_2 is weight of oven-dried grind samples with crucibles, and W_3 the weight of ash with crucibles; 0.58 is the content of carbon in dry organic matter (Allen et al. 1986).

The carbon stock in leaves, branches and stems of each individual tree was calculated separately and summed up to determine the total organic carbon stock for each individual tree.

2.5 Data analysis

Biomass data were screened for outliers in scatter plots that assisted also in visually assessing the relationships between dependent variables (aboveground biomass and the biomass of components) and independent variables (basal diameter, crown diameter, DBH and total tree height). We examined the relationship between dependent variables and independent variables using linear, logarithmic, exponential and power models. Scatter plots were set to identify the theoretical distribution that fitted well with the data. As a result, the power law model (Eq. 3) outperformed the linear, logarithmic and exponential models; and therefore, was used to fit the biomass data. We, therefore, developed site-specific allometric models for each of the tree biomass components (leaf, branch, and stem) using the following linearized form of the power-law model (Eq. 4).

$$Y = \beta_0 \times X^{\beta_1} \times \varepsilon \ , \tag{3}$$

where Y denotes the leaf biomass, branch biomass or stem biomass; X stands for D_{20}, DBH or CD; β_0 and β_1 the parameters, and ε is the random error.

This model was logarithmically transformed into its linear equivalent form defined as followed:

$$\ln(Y) = \ln(\beta_0) + \beta_1 \ln(X) + \varepsilon' \ , \tag{4}$$

where ε' is the additive error.

Based on the selected aboveground biomass model, we developed allometric models for stem, branch, leaves and aboveground components based on (i) DBH or basal diameter as lone predictor variable, (ii) $DBH^2 \times H$, and (iii) $DBH^2 \times H$ and CD, as independent variables for equation (5), (6) and (7), respectively:

$$\ln(Yi) = \ln(\beta_0) + \beta_1 \times \ln(DBH) + \varepsilon \ , \tag{5}$$

$$\ln(Yi) = \ln(\beta_0) + \beta_1 \times \ln(DBH^2 \times H) + \varepsilon \ , \tag{6}$$

$$\ln(Yi) = \ln(\beta_0) + \beta_1 \times \ln(DBH^2 \times H) + \gamma \ln(CD) + \varepsilon \ , \tag{7}$$

where Yi represents stem biomass, branch biomass and leaf biomass.

We tested whether additional use of total height or/and crown diameter as predictor would improve the precision of the prediction. As separate use of potentially correlated independent variables in regression models could give rise to collinearity (Sileshi 2014), we only considered the allometric model that combined DBH (or basal diameter) with tree height and crown diameter as single predictor variable. DBH and height were used as combined predictor to account for variation of height for the same value of diameter while solving collinearity issue in linear regression (Dimobe et al. 2018a).

The use of natural logarithmic transformations helped to normalize the response variable, and thus to meet the prerequisites of linear regression for simple estimation of the parameters (Dimobe et al. 2018a). However, the use of natural logarithmic transformations, induces a systematic bias in the final estimation of the response variable, which can generally be corrected (predicted values were back-transformed into the original values) by applying the correction factor (Baskerville 1972):

$$\mathrm{CF} = \exp\left(\mathrm{RSE}^2/2\right) , \tag{8}$$

where RSE is the residual standard error of the regression.

Normality and homoscedasticity of the residuals were tested using the Shapiro-Wilks normality and Breusch-Pagan tests, respectively. The performance of the fitted models was compared using adjusted determination coefficient (R^2), residual standard error (RSE), Akaike information criterion (AIC), a likelihood criterion that penalizes the number of parameters (Burnham and Anderson, 2002) and root mean squared error (RMSE), calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\mathrm{AGB_{obs}} - \mathrm{AGB_{est}}\right)^2}\ , \tag{9}$$

where $\mathrm{AGB_{obs}}$ is the observed AGB and $\mathrm{AGB_{est}}$ is the estimated AGB.

The site-specific AGB models were compared to four published global models in predicting the individual AGB. Published models selected were:

1. $\widehat{\mathrm{AGB}} = 0.0673 \times \left(\rho \times \mathrm{DBH}^2 \times \mathrm{H}\right)^{0.976}$ by Chave et al. (2014) for pantropical forests,

where AGB is the aboveground biomass per tree in kg per tree, DBH is the diameter at breast height, ρ is wood density in g cm^{-3}, and H is the total height of the tree.

2. $\widehat{\mathrm{AGB}} = 0.0776 \times \left(\rho \times \mathrm{DBH}^2 \times \mathrm{H}\right)^{0.940}$ by Chave et al. (2005) for dry forest stands.

3. $\widehat{\mathrm{AGB}} = 0.016 \times \left(\left(\mathrm{H} \times \mathrm{CD}\right)^{2.013}\right) e^{\frac{0.204^2}{2}}$ a global tree model proposed by Jucker et al. (2017) for angiosperms, using tree height and crown diameter as predictive variables,

where AGB is the aboveground biomass per tree in kg per tree, H is the total height of the tree, and CD is the mean crown diameter.

4. $\widehat{\mathrm{AGB}} = \left(13.2579 - \left(4.8945 \times \mathrm{DBH}\right) + 0.6713 \times \mathrm{DBH}^2\right)$ a model proposed by Brown et al. (1989), using DBH as the only predictor.

Differences between the selected model developed in this study and published models were assessed graphically, and the models were also compared using adjusted R^2, RMSE and mean prediction error. The average relative systematic error was calculated as follow:

$$\text{Mean predictionerror} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\mathrm{AGB_{est}} - \mathrm{AGB_{obs}}}{\mathrm{AGB_{obs}}}\right) \times 100\ ,$$

where $\mathrm{AGB_{est}}$ and $\mathrm{AGB_{obs}}$ are the estimated and observed aboveground biomass, respectively.

The significance of the estimated parameters at $\alpha < 0.05$ was considered. Allometric models with greater adjusted R^2, and smaller RMSE and AIC were considered to be the best fitting.

All statistical analyses were performed using R statistical software version 3.4.2 (R Core Team 2018).

3 Results

3.1 Allometric models for estimating stem, branch and leaf biomass

Allometric models fitted to stem, branch and leaf biomass of *Diospyros mespiliformis* showed AIC values between 7.35 and 34.79, adjusted R^2 between 64.93 and 96.70, and RMSE between 0.256 and 0.677 (Table 3). Candidate allometric models and their regression coefficients are presented in Table 3. The coefficients of log-transformed allometric biomass models were significant for all biomass components ($p < 0.001$, Table 3). In general, the fitted allometric models for the biomass components were more accurate for branch and stem biomass than for foliage biomass (Table 3). For instance, the fitted models explained more than 90% of the total variations, except for leaf. Stem biomass was more accurate predicted in Tiogo and Tapoa-Boopo when DBH and height were used

Table 3. Allometric models developed for estimation of biomass of stem, branches and leaves of *Diospyros mespiliformis* in Burkina Faso. ln(β_0), β_1 and γ represent the intercept and regression coefficients of the models, and their respective standard errors. The indicators of performance for the models include the adjusted coefficient of determination (Adj.R^2), residual standard error (RSE), root mean squared error (RMSE), Akaike information criterion (AIC) and correction factor (CF).

		Regression coefficients			Performance criteria				
Equation	Predictors	ln(β_0)	β_1	γ	Adj.R^2	RSE	RMSE	AIC	CF
Boulon (Sudanian zone)									
Stem biomass									
Eq(5)	DBH	$-3.25^{***}\pm0.48$	$2.22^{***}\pm0.15$		94.70	0.327	0.300	11.62	1.055
	D20	$\mathbf{-4.27^{***}\pm0.48}$	$\mathbf{2.39^{***}\pm0.14}$		**96.02**	**0.283**	**0.260**	**07.89**	**1.041**
	CD	$0.29^{ns}\pm0.53$	$2.14^{***}\pm0.31$		79.85	0.637	0.586	28.98	1.225
Eq(6)	$DBH^2\times H$	$-3.08^{**}\pm0.84$	$0.84^{***}\pm0.10$		84.83	0.552	0.508	25.28	1.165
	$DBH^2\times CD$	$-2.22^{***}\pm0.49$	$0.76^{***}\pm0.06$		92.76	0.382	0.351	15.68	1.076
	$D20^2\times H$	$-3.68^{**}\pm0.96$	$0.87^{***}\pm0.11$		83.61	0.574	0.528	26.29	1.179
	$D20^2\times CD$	$-2.85^{***}\pm0.51$	$0.79^{***}\pm0.06$		93.59	0.359	0.330	14.09	1.067
Eq(7)	$DBH^2\times H$; CD	$-2.11^{ns}\pm1.14$	$0.56^{*}\pm0.24$	$0.78^{ns}\pm0.65$	85.48	0.540	0.474	25.48	1.157
	$D20^2\times H$; CD	$-2.37^{ns}\pm1.28$	$0.54^{ns}\pm0.24$	$0.90^{ns}\pm0.62$	85.17	0.546	0.479	25.75	1.161
Branch biomass									
Eq(5)	DBH	$-4.47^{***}\pm0.64$	$2.73^{***}\pm0.20$		93.93	0.591	0.395	18.77	1.097
	D20	$-5.58^{***}\pm0.81$	$2.89^{***}\pm0.24$		92.37	0.482	0.444	21.76	1.123
	CD	$-0.32^{ns}\pm0.50$	$2.76^{***}\pm0.29$		87.91	0.607	0.558	27.73	1.202
Eq(6)	$DBH^2\times H$	$-4.62^{***}\pm0.72$	$1.07^{***}\pm0.09$		92.49	0.478	0.440	21.55	1.121
	$\mathbf{DBH^2\times CD}$	$\mathbf{-3.32^{***}\pm0.50}$	$\mathbf{0.94^{***}\pm0.06}$		**95.03**	**0.389**	**0.358**	**16.18**	**1.079**
	$D20^2\times H$	$-5.32^{***}\pm0.95$	$1.10^{***}\pm0.11$		89.42	0.568	0.522	26.00	1.175
	$D20^2\times CD$	$-4.02^{***}\pm0.60$	$0.98^{***}\pm0.07$		94.06	0.425	0.391	18.49	1.095
Eq(7)	$DBH^2\times H$; CD	$-3.30^{**}\pm0.87$	$0.69^{**}\pm0.19$	$1.08^{ns}\pm0.49$	94.41	0.413	0.362	18.46	1.089
	$D20^2\times H$; CD	$-3.36^{*}\pm1.08$	$0.62^{*}\pm0.21$	$1.34^{*}\pm0.52$	93.00	0.462	0.405	21.39	1.112
Leaf biomass									
Eq(5)	DBH	$-3.71^{***}\pm0.58$	$2.09^{***}\pm0.18$		91.65	0.390	0.359	16.26	1.079
	D20	$-4.58^{***}\pm0.70$	$2.22^{***}\pm0.21$		90.48	0.417	0.383	17.97	1.091
	CD	$-0.53^{ns}\pm0.43$	$2.10^{***}\pm0.25$		84.94	0.524	0.482	23.92	1.147
Eq(6)	$DBH^2\times H$	$-3.85^{***}\pm0.62$	$0.82^{***}\pm0.07$		90.76	0.411	0.378	17.57	1.088
	$\mathbf{DBH^2\times CD}$	$\mathbf{-2.82^{***}\pm0.48}$	$\mathbf{0.72^{***}\pm0.06}$		**92.44**	**0.371**	**0.342**	**14.97**	**1.071**
	$D20^2\times H$	$-4.39^{***}\pm0.78$	$0.85^{***}\pm0.09$		88.05	0.467	0.429	20.92	1.115
	$D20^2\times CD$	$-3.37^{***}\pm0.55$	$0.75^{***}\pm0.06$		91.73	0.389	0.357	16.14	1.078
Eq(7)	$DBH^2\times H$; CD	$-2.95^{**}\pm0.81$	$0.56^{**}\pm0.17$	$0.74^{ns}\pm0.46$	91.93	0.384	0.336	16.58	1.076
	$D20^2\times H$; CD	$-3.03^{*}\pm0.97$	$0.51^{*}\pm0.19$	$0.93^{ns}\pm0.47$	90.60	0.414	0.363	18.56	1.090
Tapoa-Boopo (Sahelo-Sudanian zone)									
Stem biomass									
Eq(5)	DBH	$-3.89^{***}\pm0.63$	$2.39^{***}\pm0.20$		92.19	0.401	0.369	16.96	1.084
	D20	$-4.37^{***}\pm0.71$	$2.40^{***}\pm0.21$		91.43	0.420	0.386	18.17	1.092
	CD	$-0.97^{ns}\pm0.64$	$2.77^{***}\pm0.38$		81.58	0.616	0.567	28.12	1.209
Eq(6)	$\mathbf{DBH^2\times H}$	$\mathbf{-4.50^{***}\pm0.51}$	$\mathbf{0.99^{***}\pm0.06}$		**95.43**	**0.307**	**0.282**	**09.99**	**1.048**
	$DBH^2\times CD$	$-3.15^{***}\pm0.61$	$0.85^{***}\pm0.08$		91.07	0.429	0.394	18.69	1.096
	$D20^2\times H$	$-4.89^{***}\pm0.59$	$0.99^{***}\pm0.07$		94.64	0.332	0.305	12.06	1.057
	$D20^2\times CD$	$-3.48^{***}\pm0.67$	$0.85^{***}\pm0.08$		90.33	0.446	0.410	19.73	1.104
Eq(7)	$DBH^2\times H$; CD	$-4.66^{***}\pm0.74$	$1.05^{***}\pm0.19$	$-0.17^{ns}\pm0.57$	95.02	0.320	0.281	11.88	1.053
	$D20^2\times H$; CD	$-5.06^{**}\pm0.89$	$1.05^{**}\pm0.21$	$-0.16^{ns}\pm0.63$	94.15	0.347	0.304	13.97	1.062
Branch biomass									
Eq(5)	DBH	$-4.99^{***}\pm0.49$	$2.83^{***}\pm0.16$		96.39	0.316	0.291	10.78	1.051
	D20	$-5.56^{***}\pm0.58$	$2.84^{***}\pm0.17$		95.65	0.347	0.319	13.21	1.062
	CD	$-1.68^{*}\pm0.54$	$3.36^{***}\pm0.32$		90.15	0.522	0.480	23.83	1.146

Table 3 continued.

Equation	Predictors	Regression coefficients $\ln(\beta_0)$	β_1	γ	Performance criteria Adj.R^2	RSE	RMSE	AIC	CF
Eq(6)	DBH^2×H	$-5.46^{***}\pm0.69$	$1.15^{***}\pm0.08$		93.97	0.408	0.376	17.44	1.087
	DBH^2×CD	**$-4.17^{***}\pm0.43$**	**$1.02^{***}\pm0.05$**		**96.70**	**0.302**	**0.278**	**09.62**	**1.047**
	D20^2×H	$-5.90^{***}\pm0.76$	$1.15^{***}\pm0.09$		93.20	0.434	0.399	19.00	1.099
	D20^2×CD	$-4.56^{***}\pm0.50$	$1.02^{***}\pm0.06$		95.96	0.334	0.307	12.23	1.057
Eq(7)	DBH^2×H; CD	$-4.34^{***}\pm0.85$	$0.76^{***}\pm0.22$	$1.23^{ns}\pm0.65$	95.12	0.367	0.322	15.45	1.069
	D20^2×H; CD	$-4.53^{**}\pm1.02$	$0.73^{*}\pm0.24$	$1.31^{ns}\pm0.71$	94.41	0.393	0.345	17.22	1.080
Leaf biomass									
Eq(5)	DBH	$-4.64^{***}\pm0.65$	$2.17^{***}\pm0.21$		90.17	0.412	0.379	17.65	1.088
	D20	$-5.09^{***}\pm0.70$	$2.18^{***}\pm0.21$		89.93	0.417	0.383	17.95	1.091
	CD	$-2.19^{*}\pm0.47$	$2.62^{***}\pm0.28$		88.10	0.453	0.417	20.12	1.108
Eq(6)	DBH^2×H	$-5.02^{***}\pm0.74$	$0.88^{***}\pm0.109$		88.63	0.443	0.407	19.53	1.103
	DBH^2×CD	**$-4.04^{***}\pm0.55$**	**$0.78^{***}\pm0.07$**		**91.60**	**0.381**	**0.350**	**15.59**	**1.075**
	D20^2×H	$-5.38^{***}\pm0.79$	$0.88^{***}\pm0.09$		88.29	0.449	0.413	19.92	1.106
	D20^2×CD	$-4.36^{***}\pm0.58$	$0.78^{***}\pm0.07$		91.24	0.389	0.357	16.14	1.078
Eq(7)	DBH^2×H; CD	$-3.85^{**}\pm0.93$	$0.47^{ns}\pm0.24$	$1.30^{ns}\pm0.71$	90.62	0.402	0.353	17.79	1.084
	D20^2×H; CD	$-3.99^{**}\pm1.06$	$0.46^{ns}\pm0.25$	$1.33^{ns}\pm0.74$	90.25	0.410	0.359	18.29	1.088
	D20^2×H; CD	$-3.82^{***}\pm0.52$	$0.84^{***}\pm0.12$	$0.76^{ns}\pm0.36$	97.09	0.201	0.176	−0.285	1.020
Tiogo (Sahelo-Sudanian zone)									
Stem biomass									
Eq(5)	DBH	$-5.11^{***}\pm0.91$	$2.75^{***}\pm0.28$		89.44	0.348	0.318	12.54	1.062
	D20	$-5.78^{***}\pm1.10$	$2.82^{***}\pm0.33$		86.95	0.387	0.353	15.08	1.078
	CD	$-0.74^{ns}\pm0.97$	$2.49^{***}\pm0.54$		64.93	0.634	0.579	26.94	1.223
Eq(6)	**DBH^2×H**	**$-5.58^{***}\pm0.93$**	**$1.09^{***}\pm0.11$**		**90.10**	**0.337**	**0.308**	**11.77**	**1.058**
	DBH^2×CD	$-3.92^{**}\pm0.95$	$0.93^{***}\pm0.12$		85.36	0.410	0.374	16.46	1.088
	D20^2×H	$-6.18^{***}\pm1.06$	$1.12^{***}\pm0.12$		88.67	0.360	0.329	13.38	1.067
	D20^2×CD	$-4.37^{***}\pm1.07$	$0.95^{***}\pm0.13$		83.71	0.432	0.395	17.74	1.098
Eq(7)	DBH^2×H; CD	$-6.02^{***}\pm1.20$	$1.23^{***}\pm0.25$	$-0.41^{ns}\pm0.66$	89.44	0.348	0.301	13.28	1.062
	D20^2×H; CD	$-6.56^{**}\pm1.44$	$1.22^{**}\pm0.28$	$-0.30^{ns}\pm0.71$	87.66	0.376	0.326	15.15	1.073
Branch biomass									
Eq(5)	DBH	$-4.58^{***}\pm0.85$	$2.80^{***}\pm0.27$		90.93	0.326	0.298	10.99	1.055
	D20	$-5.32^{***}\pm1.00$	$2.89^{***}\pm0.29$		89.49	0.351	0.321	12.75	1.064
	CD	$-0.63^{ns}\pm0.66$	$2.83^{***}\pm0.37$		84.16	0.431	0.394	17.68	1.097
Eq(6)	DBH^2×H	$-4.98^{***}\pm0.94$	$1.11^{***}\pm0.11$		90.08	0.341	0.312	12.06	1.060
	DBH^2×CD	**$-3.63^{***}\pm0.65$**	**$0.98^{***}\pm0.08$**		**93.30**	**0.280**	**0.256**	**07.35**	**1.040**
	D20^2×H	$-5.63^{***}\pm1.03$	$1.14^{***}\pm0.12$		89.46	0.352	0.321	12.79	1.064
	D20^2×CD	$-4.13^{***}\pm0.73$	$1.00^{***}\pm0.09$		92.50	0.297	0.271	08.69	1.045
Eq(7)	DBH^2×H; CD	$-3.77^{***}\pm1.04$	$0.73^{***}\pm0.22$	$1.10^{*}\pm0.57$	92.19	0.303	0.262	09.92	1.047
	D20^2×H; CD	$-4.13^{**}\pm1.19$	$0.74^{*}\pm0.23$	$1.15^{ns}\pm0.59$	91.80	0.310	0.269	10.52	1.049
Leaf biomass									
Eq(5)	DBH	$-4.90^{***}\pm1.07$	$2.23^{***}\pm0.33$		80.10	0.407	0.372	16.30	1.086
	D20	$-5.31^{**}\pm1.31$	$2.25^{***}\pm0.38$		74.64	0.459	0.419	19.19	1.111
	CD	$-1.84^{*}\pm0.66$	$2.29^{***}\pm0.37$		77.52	0.433	0.395	17.76	1.098
Eq(6)	DBH^2×H	$-5.27^{***}\pm1.11$	$0.89^{***}\pm0.13$		80.36	0.405	0.369	16.14	1.085
	DBH^2×CD	**$-4.18^{**}\pm0.86$**	**$0.79^{***}\pm0.10$**		**83.41**	**0.372**	**0.339**	**14.11**	**1.072**
	D20^2×H	$-5.64^{**}\pm1.30$	$0.89^{***}\pm0.15$		76.53	0.442	0.404	18.28	1.103
	D20^2×CD	$-4.48^{**}\pm1.01$	$0.79^{***}\pm0.12$		79.82	0.410	0.374	16.46	1.088
Eq(7)	DBH^2×H; CD	$-4.11^{*}\pm1.32$	$0.53^{*}\pm0.28$	$1.05^{ns}\pm0.73$	82.26	0.384	0.333	15.65	1.077
	D20^2×H; CD	$-3.98^{*}\pm1.57$	$0.45^{ns}\pm0.30$	$1.27^{ns}\pm0.77$	79.97	0.408	0.354	17.11	1.087

Models selected as most appropriate are indicated in bold.

($DBH^2 \times H$) as compound variable (Table 3) than in Boulon. In Boulon, stem biomass was more accurately predicted using basal diameter (D20) alone than in Tiogo and Tapoa-Boopo. Similarly, leaf biomass was more accurately predicted when using DBH and crown diameter ($DBH^2 \times CD$) as single variable in Tiogo and Tapoa-Boopo while in Boulon addition of crown diameter to basal diameter as compound variable ($D20^2 \times CD$) provided accurate estimation of leaf biomass (Table 3). However, in the three sites, branch biomass was more accurately predicted when DBH and crown diameter were used as compound variable (Table 3). The predictive ability and accuracy of these models are demonstrated by the homoscedastic trend and good coincidence to the $y = x$ linear equation shown in the diagnostic graphs of residuals (and observed values) versus predicted values of stem biomass, branch biomass and leaf biomass (Fig. 2).

3.2 Allometric models for estimating aboveground biomass

For each study site, nine allometric models were developed for aboveground biomass (AGB). Metrics for evaluation the performance of candidate allometric models developed for estimating AGB of *D. mespiliformis* in Burkina Faso are presented in Table 4. The adjusted coefficient of determination for the selected models was greater, explaining between 92.26–98.92% of the variance observed in the biomass. The AIC and RMSE values ranged from –9.02 to 21.76 and 0.119 to 0.425, respectively. In the three sites, DBH alone was the most suitable predictor variable than basal diameter and crown diameter for AGB (Table 3). Compared with model based on DBH as single predictor, adding tree total height to DBH as compound variable ($DBH^2 \times H$) did not significantly improve the statistical fits (Table 4). However, addition of DBH to crown diameter and height as compound variable ($DBH^2 \times H \times CD$) in Tiogo and Tapoa-Boopo reduced the RMSE, AIC and RSE and made further significant change except in Boulon where DBH provided greater adjusted R^2, smaller RSE, smaller RMSE and smaller AIC (Table 3 and 4). Graphs of residuals (and observed values) versus predicted values of aboveground biomass for the selected models (Fig. 3) suggested homogeneity of residuals and $y = x$ linear trend. These results indicate that the selected models were the most suitable and can be used to predict aboveground biomass of *D. mespiliformis* in the study area.

3.3 Performance of published models

Models developed in this study performed more accurately than published models for general purpose (Figs. 4a,4b,4c). The performance of models developed in this study was comparable to that of Brown (1997) in terms of RMSE. However, it had less mean prediction error and greater adjusted R^2 (Fig. 4a). The model by Brown (1989) had the less RMSE but a greater mean prediction error (+97.18%; +80.34% ; and +60.92% for Tapoa-Boopo; Tiogo and Boulon respectively), while the models developed in this study presented comparatively a greater adjusted R^2 and the lowest average systematic bias (+2.28%; +3.10% and –3.28% for Tiogo; Tapoa-Boopo and Boulon respectively). The comparison of model developed by Chave et al. (2014) with Brown's model showed that Chave et al.'s model fitted the data more accurately than the model of Brown (1989), which leads to an overestimation of observed AGB (Figs. 4a,4b,4c). The model proposed by Jucker et al. (2017) was the least appropriate; it generally underestimated aboveground biomass with greater RMSE and average systematic bias. Compared to the model developed in this study, Brown's model greatly overestimated the observed AGB, while the Jucker et al.'s underestimated it.

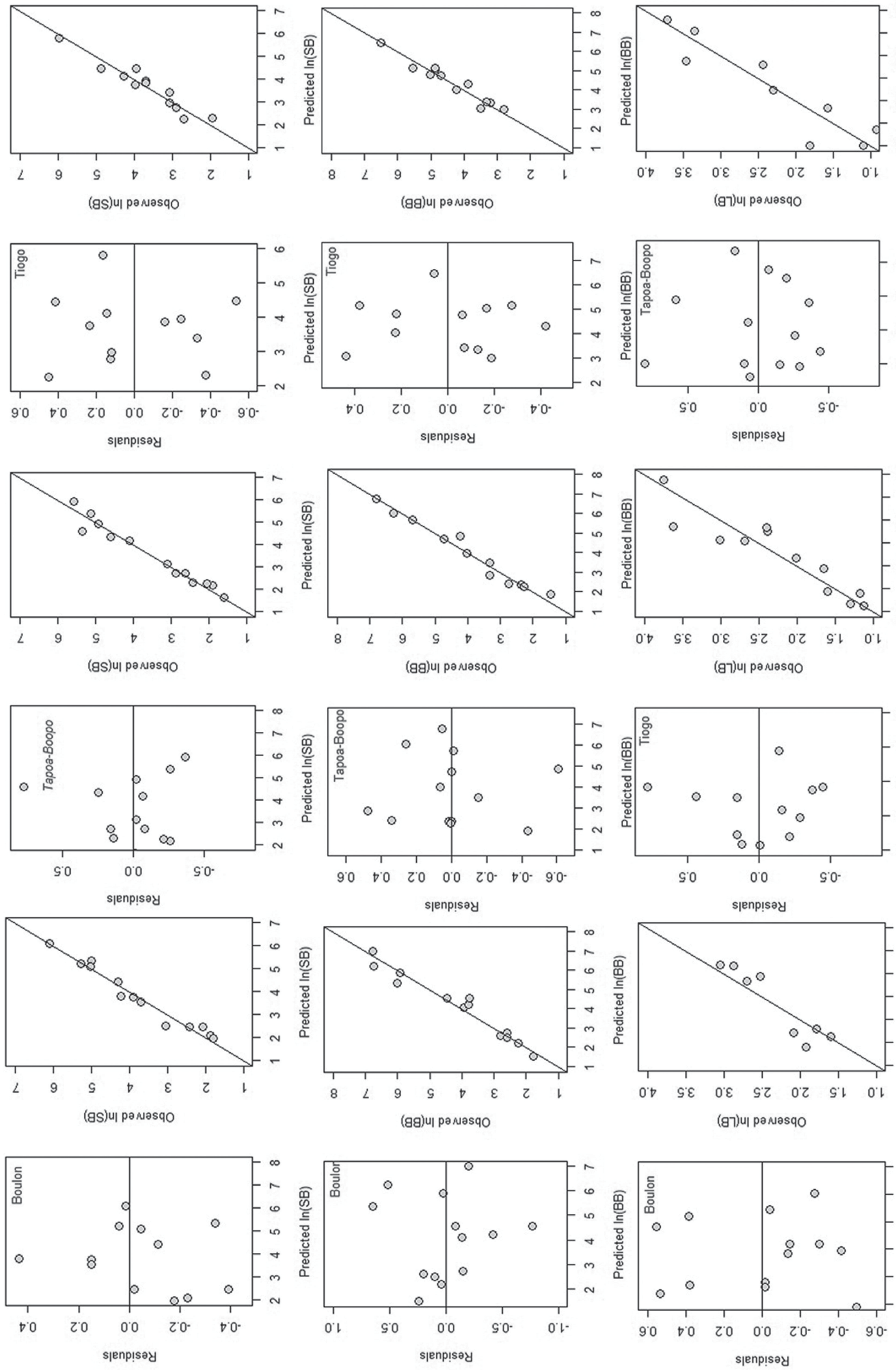

Fig. 2. Residuals and observed values versus predicted values of stem (SB), branch (BB) and leaf biomass (LB) for Boulon, Tapoa-Boopo and Tiogo forests, respectively.

Table 4. Site-specific allometric equations for estimating aboveground biomass of *Diospyros mespiliformis* in Burkina Faso. $\ln(\beta_0)$, β_1 and γ represent the intercept and regression coefficients of the models, and their respective standard errors. The indicators of performance for the models include the adjusted coefficient of determination (Adj.R^2), residual standard error (RSE), root mean squared error (RMSE), Akaike information criterion (AIC) and correction factor (CF).

		Regression coefficients				Performance criteria				
Equation N°	Predictors	$\ln(\beta_0)$	β_1	γ	Models	Adj.R^2	RSE	RMSE	AIC	CF
Boulon (Sudanian zone)										
Eq(5)	**DBH**	$\mathbf{-2.97^{***}\pm0.39}$	$\mathbf{2.48^{***}\pm0.12}$		**Y=1.036×exp (–2.97+2.48 ln (DBH))**	**97.11**	**0.266**	**0.245**	**06.30**	**1.036**
	D20	$-4.02^{***}\pm0.50$	$2.65^{***}\pm0.15$		Y=1.045×exp (–4.02+2.65 ln (D20))	96.39	0.297	0.274	09.19	1.045
	CD	$-0.87^{ns}\pm0.46$	$2.46^{***}\pm0.27$		Y=1.228×exp (–0.87+2.46 ln (CD))	87.38	0.556	0.594	25.47	1.228
Eq(6)	DBH^2×H	$-2.99^{***}\pm0.66$	$0.96^{***}\pm0.08$		Y=1.097×exp (–2.99+0.96 ln (DBH^2×H))	92.42	0.431	0.396	18.84	1.097
	DBH^2×CD	$-1.39^{***}\pm0.35$	$0.85^{***}\pm0.04$		Y=1.037×exp (–1.39+0.85 ln (DBH^2×CD))	97.03	0.270	0.248	06.65	1.037
	$D20^2$×H	$-3.64^{**}\pm0.83$	$0.99^{***}\pm0.09$		Y=1.133×exp (–3.64+0.99 ln ($D20^2$×H))	89.83	0.499	0.459	22.66	1.133
	$D20^2$×CD	$-2.55^{***}\pm0.41$	$0.89^{***}\pm0.05$		Y=1.043×exp (–2.55+0.89 ln ($D20^2$×CD))	96.59	0.289	0.266	08.46	1.043
Eq(7)	DBH^2×H; CD	$-1.85^{*}\pm0.80$	$0.64^{**}\pm0.17$	$0.93^{ns}\pm0.45$	Y=1.074×exp (–1.85+0.64 ln (DBH^2×H) + 0.93 ln (CD))	94.14	0.379	0.332	16.26	1.074
	$D20^2$×H; CD	$-1.97^{ns}\pm0.97$	$0.58^{*}\pm0.19$	$1.14^{ns}\pm0.47$	Y=1.090×exp (–1.97+0.58 ln ($D20^2$×H) + 1.14 ln (CD))	92.99	0.415	0.364	18.59	1.090
Tapoa-Boopo (Sahelo-Sudanian zone)										
Eq(5)	DBH	$-3.66^{***}\pm0.29$	$2.64^{***}\pm0.09$		Y=1.018×exp (–3.66+2.64 ln (DBH))	98.50	0.188	0.173	–02.12	1.018
	D20	$-4.20^{***}\pm0.37$	$2.65^{***}\pm0.11$		Y=1.024×exp (–4.20+2.65 ln (D20))	97.98	0.218	0.201	01.12	1.024
	CD	$-0.55^{ns}\pm0.47$	$3.11^{***}\pm0.28$		Y=1.110×exp (–0.55+3.11 ln (CD))	91.12	0.457	0.420	20.36	1.110
Eq(6)	DBH^2×H	$-4.19^{***}\pm0.33$	$1.08^{***}\pm0.04$		Y=1.020×exp (–4.19+1.08 ln (DBH^2×H))	98.34	0.198	0.182	–01.42	1.020
	DBH^2×CD	$-2.89^{***}\pm0.27$	$0.95^{***}\pm0.03$		Y=1.018×exp (–2.89+0.95 ln (DBH^2×CD))	98.50	0.188	0.173	–02.78	1.018
	$D20^2$×H	$-4.62^{***}\pm0.41$	$1.08^{***}\pm0.05$		Y=1.027×exp (–4.62+1.08 ln ($D20^2$×H))	97.75	0.230	0.212	02.52	1.027
	$D20^2$×CD	$-3.26^{***}\pm0.33$	$0.95^{***}\pm0.04$		Y=1.025×exp (–3.26+0.95 ln ($D20^2$×CD))	97.92	0.221	0.203	01.46	1.025
Eq(7)	**DBH^2×H; CD**	$\mathbf{-3.52^{***}\pm0.37}$	$\mathbf{0.85^{***}\pm0.09}$	$\mathbf{0.74^{*}\pm0.28}$	**Y=1.013×exp (–3.52+0.85 ln (DBH^2×H) + 0.74 ln (CD))**	**98.92**	**0.159**	**0.139**	**–06.28**	**1.013**
	$D20^2$×H; CD	$-3.82^{***}\pm0.52$	$0.84^{***}\pm0.12$	$0.76^{ns}\pm0.36$	Y=1.020×exp (–3.82+0.84 ln ($D20^2$×H) + 0.76 ln (CD))	97.09	0.201	0.176	–0.285	1.020
Tiogo (Sahelo-Sudanian zone)										
Eq(5)	DBH	$-3.86^{***}\pm0.40$	$2.74^{***}\pm0.12$		Y=1.012×exp (–3.86+2.74 ln (DBH))	97.77	0.153	0.139	–07.16	1.012
	D20	$-4.55^{***}\pm0.63$	$2.81^{***}\pm0.19$		Y=1.024×exp (–4.55+2.81 ln (D20))	95.41	0.219	0.200	01.47	1.024
	CD	$0.16^{ns}\pm0.63$	$2.67^{***}\pm0.35$		Y=1.088×exp (0.16+2.67 ln (CD))	83.99	0.410	0.374	16.47	1.088
Eq(6)	DBH^2×H	$-4.28^{***}\pm0.45$	$1.09^{***}\pm0.05$		Y=1.013×exp (–4.28+1.09 ln (DBH^2×H))	97.46	0.164	0.149	–05.60	1.013
	DBH^2×CD	$-2.84^{***}\pm0.34$	$0.95^{***}\pm0.04$		Y=1.010×exp (–2.84+0.95 ln (DBH^2×CD))	98.00	0.145	0.132	–08.49	1.010
	$D20^2$×H	$-4.89^{***}\pm0.59$	$1.12^{***}\pm0.07$		Y=1.020×exp (–4.89+1.12 ln ($D20^2$×H))	96.16	0.201	0.183	–0.67	1.020
	$D20^2$×CD	$-3.31^{***}\pm0.47$	$0.96^{***}\pm0.05$		Y=1.018×exp (–3.31+0.96 ln ($D20^2$×CD))	96.54	0.191	0.174	–01.89	1.018
Eq(7)	**DBH^2×H; CD**	$\mathbf{-3.63^{***}\pm0.47}$	$\mathbf{0.89^{***}\pm0.10}$	$\mathbf{0.59^{*}\pm0.26}$	**Y=1.009×exp (–3.63+0.89 ln (DBH^2×H) + 0.59 ln (CD))**	**98.20**	**0.137**	**0.119**	**–09.02**	**1.009**
	$D20^2$×H; CD	$-4.01^{***}\pm0.67$	$0.88^{***}\pm0.13$	$0.67^{ns}\pm0.33$	Y=1.015×exp (–4.01+0.88 ln ($D20^2$×H) + 0.67 ln (CD))	97.09	0.175	0.151	–03.25	1.015

Models selected are indicated in bold.

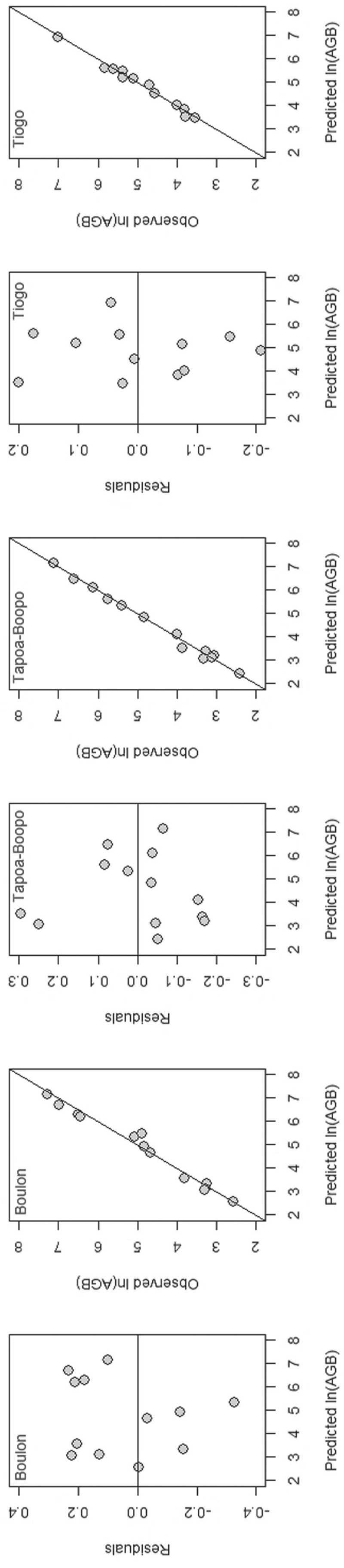

Fig. 3. Residuals and observed values versus predicted values of aboveground biomass (AGB) in Boulon, Tapoa-Boopo and Tiogo.

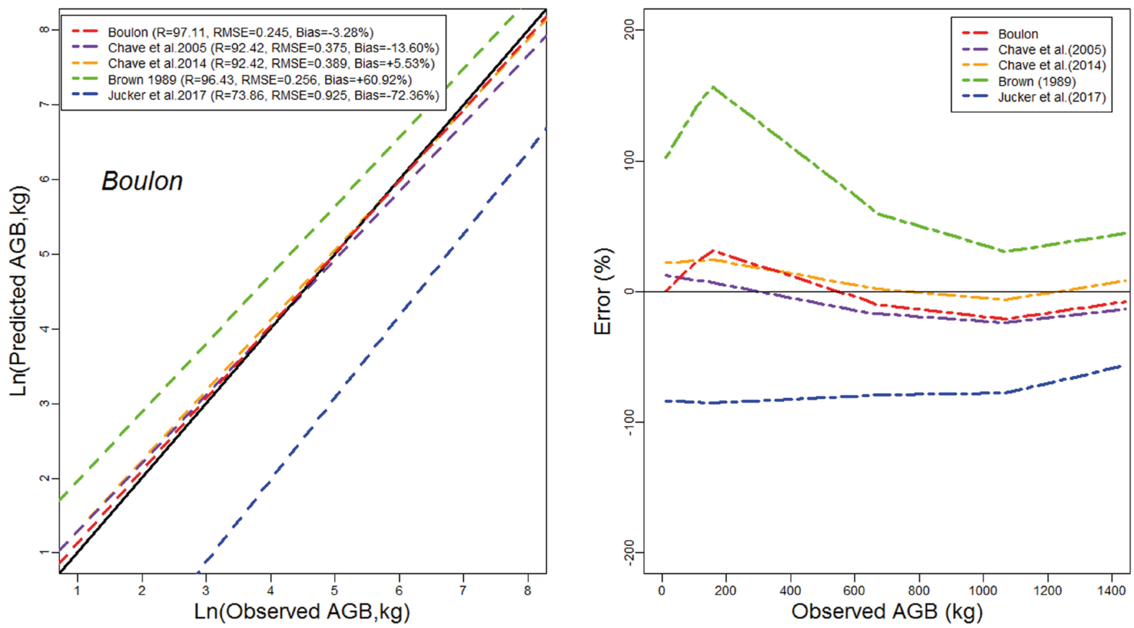

Fig. 4a. Comparison of models' performances using the fitting dataset in Boulon. (left) Predicted and observed aboveground biomass values for the selected models. (right) Mean relative errors for the compared models across the observed aboveground biomass values.

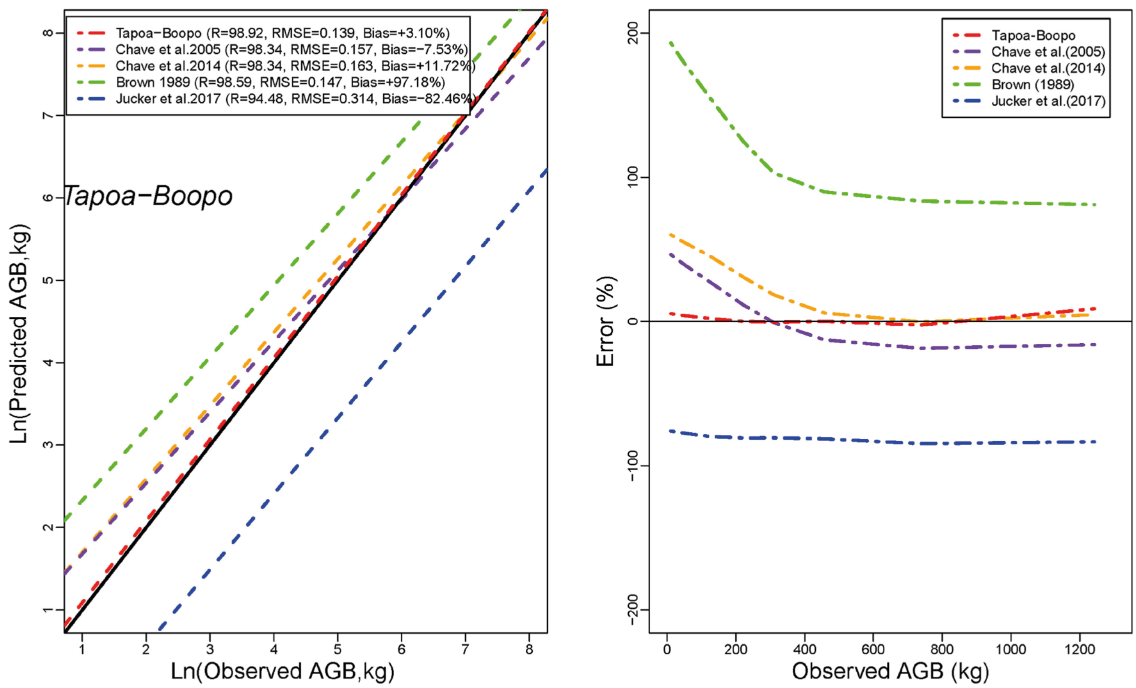

Fig. 4b. Comparison of models' performances using the fitting dataset in Tapoa-Boopo. (left) Predicted and observed aboveground biomass values for the selected models. (right) Mean relative errors for the compared models across the observed aboveground biomass values.

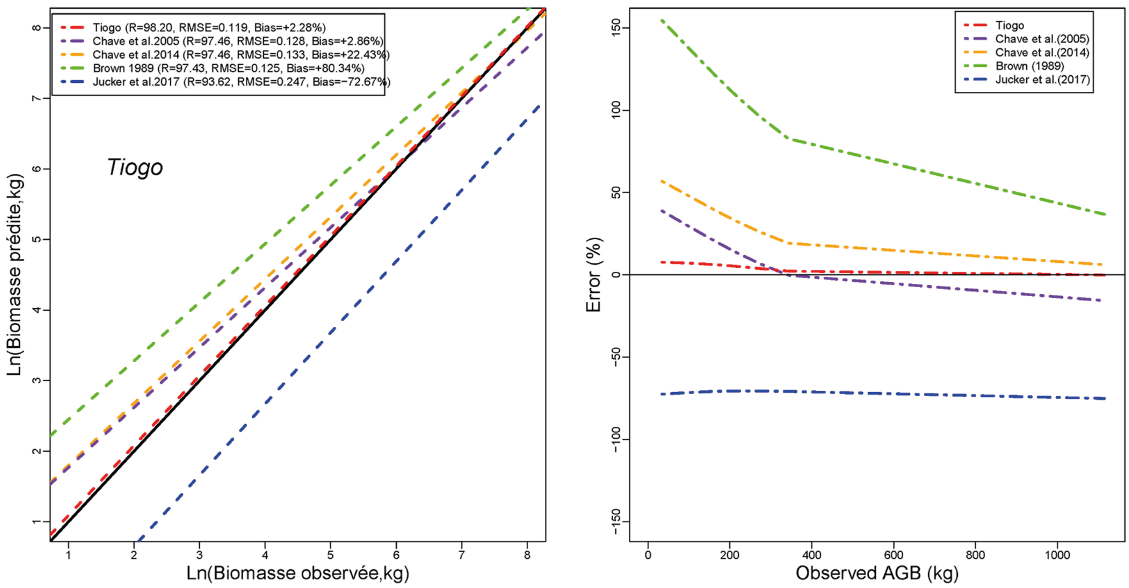

Fig. 4c. Comparison of models' performances using the fitting dataset in Tiogo. (left) Predicted and observed aboveground biomass values for the selected models. (right) Mean relative errors for the compared models across the observed aboveground biomass values.

3.3 Carbon content of *Diospyros mespiliformis* tree components

Carbon content in aboveground components of *Diospyros mespiliformis* in Tiogo, Boulon and Tapoa-Boopo was 55.40% ± 1.50, 55.52% ± 1.06 and 55.63% ± 1.00, respectively, and did not vary significantly (*P*-value = 0.909). The Fig. 5 showed that stem had the largest carbon content in Tapoa-Boopo (56.24 ± 0.61%) and Tiogo (56.72 ± 0.27%) while in Boulon the largest carbon content is stored in branches (55.95 ± 0.07%). Leaves had the smallest amount of carbon content in the three sites (Fig. 5). The mean carbon stocks were 125.13 kg C tree^{-1} (±164.9) in Boulon, 141.48 kg C tree^{-1} (±15.74) in Tapoa-Boopo and 190.77 kg C tree^{-1} (±19.84) in Tiogo.

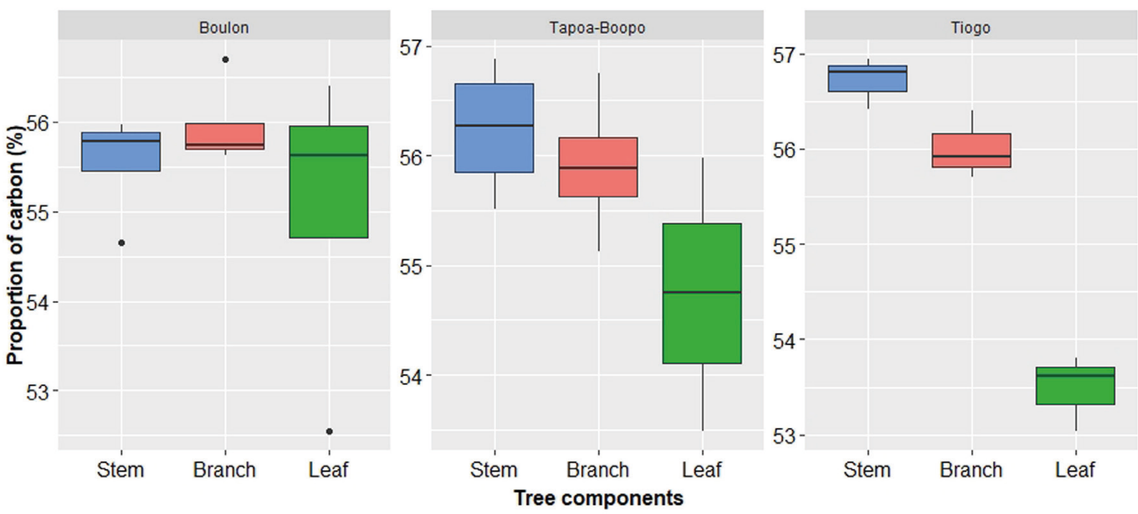

Fig. 5. Carbon content in *Diospyros mespiliformis* tree components (from 5 samples) in Boulon, Tapoa-Boopo and Tiogo forests.

4 Discussion

4.1 Allometric biomass components models

Several allometric models for estimating tree components' biomass are used to describe the relationship between tree parameters and biomass (Kuyah et al. 2014; Mensah et al. 2016; Dimobe et al. 2018b). Power law model was used in this study to predict tree components' biomass. This result is consistent with previous reports (Xiang et al. 2016; Dimobe et al. 2018a). The models tested to estimate the relationships between biomass and explanatory variables are of the log-log form, which have been shown to predict the biomass of woody species with great accuracy (Chaturvedi et al. 2013). Chave et al. (2005) pointed out that biological data are heteroskedastic and that it is necessary to log-transform the variables to comply with the conditions of normality and homoscedasticity. The explained variance of the fitted allometric models at stem, branch and leaf level, ranging from 81.41% to 98.92% and was smaller for leaf biomass models than for branch and stem biomass models, as also reported by Mensah et al. (2017) and Morote et al. (2012) in previous studies. These results indicate that foliage allometries are less responsive to tree size than are branch and stem allometries(Dimobe et al. 2018a). This is probably because leaves are more sensitive to light exposure than branches and stem (Antin et al. 2013). These results also showed that the predictors for biomass components were not the same in the three sites. DBH and height used as compound variable appears to be good predictor for stem biomass in Tapoa-Boopo and Tiogo (Sahelo-Sudanian zone) whereas in Boulon (Sudanian zone), the reliable predictor is basal diameter. This finding accords with that of Balima et al. (2019) who also found in Burkina Faso that basal diameter is a good predictor for the stem biomass of *Afzelia Africana* in the Sudanian zone whereas in Sahelo-Sudanian zone, it was basal diameter and height ($D20^2 \times h$), indicating that stem biomass vary according to climatic gradient. The somewhat smaller adjusted R^2 values for component biomass in Sudanian zone compared to Sahelo-Sudanian zone seen in this study have also been reported by Balima et al (2019). The additional use of height and crown diameter in this study is expected to account for variation in biomass of trees having the same diameter. The inclusion of tree height as additional predictor in allometric models was studied by Picard et al. (2015) and Dimobe et al. (2018a). It helps accounting for variation in AGB among trees with same value of DBH (Picard et al. 2015), thus reducing the estimate errors (Chave et al. 2005). For instance, in this study, inclusion of tree height as additional predictor improved the models for stem biomass for both Tapoa-Boopo and Tiogo. Dimobe et al. (2018a) reported improved biomass models due to inclusion of tree height. Moreover, according to Mensah et al. (2017), the use of $DBH^2 \times H$ as compound variable helps avoiding collinearity issues while accounting for within species variation of height for a given value of DBH. Other authors recommend the use of wood density, crown diameter, and site as additional predictor variables to improve biomass prediction (Chave et al. 20005; Fayole et al. 2013; Ngomanda et al. 2014; Chave et al. 2014;). We found in this study that inclusion of crown diameter reduced the RMSE of branch and leaf biomass estimates and improved the goodness of fit for the three sites.

4.2 Aboveground biomass model

In this study, nine allometric models were tested for their relative performance in predicting aboveground biomass. These models were satisfactory for predicting the AGB with explained variance ranging from 87 to 95%. Among the candidate allometric models, only the one with DBH as single predictor in Boulon (Sudanian zone) and the compound variable ($CD \times DBH^2 \times h$) in Tapoa-Boopo and Tiogo (Sahelo-Sudanian zone) appeared to be the most suitable for estimating the total aboveground biomass of *D. mespiliformis*. This concurs with for instance, Balima et al (2019) who found that DBH is the reliable predictor of AGB of *Afzelia africana* in the Sudanian zone of Burkina Faso while in the Sahelo-Sudanian zone it is $DBH^2 \times CD$. The difference in terms of predictors used in the two climatic zones might be due to rainfall impact on growth and morphology on individual trees of *D. mespiliformis*. In Boulon, the model with DBH as single predictor produced greater adjusted coefficient of determination ($R^2 = 97.11\%$) compared to the other predictors. This finding is in line with previous study that showed that DBH is the most commonly used independent variable (Henry et al. 2011; Mbow et al. 2013; Vahedi et al. 2014) since it is the easiest tree variable to measure. However, according to other authors such as Alvarez et al. (2012), models based on DBH only may underestimate the aboveground biomass and may show uncertainty. In Tapoa-Boopo and Tiogo, it was expected that the addition of tree height and crown diameter to DBH will improve the estimates of the allometric models. To account for that, the inclusion of tree height, crown diameter and DBH ($CD \times DBH^2 \times h$) in the allometric models as a compound predictor reduced the RMSE, RSE and AIC, and produced greater adjusted R^2 in Tapoa-Boopo and Tiogo. Although the differences were small, the selected biomass models with $CD \times DBH^2 \times h$ as compound variable performed slightly more accurately in terms of adjusted R^2, RSE, RMSE and AIC than the model with DBH alone.

4.3 Comparison with previously published models

We compared the models developed in this study with four previously published models developed by Brown et al. (1989), Chave et al. (2005), Chave et al. (2014), and Jucker et al. (2017). We choose these models for comparison with our own model because they are commonly used for biomass estimation in Burkina Faso by previous studies (Qasim et al. 2016; Dimobe et al. 2018d; Dimobe et al. 2019). The general lack of agreement between the models developed for *D. mespiliformis* in this study and the generic models, can only be viewed as discouraging. Actually, the previously published models of Brown et al. (1989), Chave et al. (2005), Chave et al. (2014), and Jucker et al. (2017) are not wrong; they are simply not right for this species or the study sites. Ducey et al. (2009) made similar observation in the eastern Amazon and found errors from –33% to +29% that occurred when using off-site relationships, indicating that site- and species specific allometric models differ with species, tree status, climate and soil (Zianis and Mencuccini 2004), and are generally preferred over generic allometric models (Montagu et al. 2005). Kim et al. (2011), in their study, emphasize that the site-specific allometric models are more accurate in predicting the forest biomass estimates on the local level as they take into account the site effects. Among the previous published models used in this study, Brown's model greatly overestimated the observed AGB when applied to our dataset, while the Jucker et al.'s model underestimated it. This suggests that the models developed in this study are adequate for AGB estimation for *D. mespiliformis* in Burkina Faso. The previous published models were widely used because of the great goodness of fit to the sample data used to develop them (Nath et al. 2019). The limitation of these site-specific models inherent to the cost of biomass measurement and they are generally based on a small sample size.

4.4 Carbon stock

In this study, the predicted values of carbon content are greater compared to the one (0.5) which was recognized as an acceptable average to be used as conversion factor (Sarmiento et al. 2005; Redondo-Brenes 2007). Hence, the application of the recommended value would underestimate the value of carbon content in leaf biomass, branch biomass, stem biomass and AGB. Our findings are consistent to the observation in Central Panama (Elias and Potvin 2003), Costa Rica (Fonseca et al. 2012), and in Burkina Faso (Bayen et al. 2015; Dimobe et al. 2018a) where authors detected underestimations of aboveground carbon when the recommended value of carbon, 0.5, is used or applied. Furthermore, our results revealed that the average carbon content varied among the different parts of the tree. It has been reported that carbon content of tree components was dependent on the ash content which in turn, depends on the amount of structural components (Negi et al. 2003). The carbon content in stems of *D. mespiliformis*, was slightly greater than the amount in branches and leaves. This can be explained by the fact that woody tissues of trunk, roots, branches and twigs were greater carbon content pools than soft tissues of leaves, flowers and fine roots (Kraenzel et al. 2003). The results are also in conformity with findings by Fonseca et al. (2012),Wani and Qaisar (2014), Bayen et al. (2015) and Dimobe et al. (2018a).

5 Conclusion

To our knowledge, this is the first attempt to develop site-specific allometric models for *Diospyros mespiliformis* in Burkina Faso. Diameter at breast height alone is a good predictor of AGB in Boulon forest (Sudanian climatic zone), while in Tapoa-Boopo and Tiogo forests (Sahelo-Sudanian climatic zone), the inclusion of crown diameter and height are required to improve the AGB predictions. The models developed in this study can be used accurately to estimate the aboveground and tree components biomass in similar environments (climatic zones). The applicability of these models is therefore restricted to the climatic zones and range of data covered by trees used in this study. The results revealed also that *D. mespiliformis* contains greater amount of carbon than the reference value suggested by the IPCC, indicating a greater potential for carbon sequestration for mitigating adverse effects of climate change over large areas of West African savannas.

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