



Conventional and additive models for estimating the biomass, carbon and nutrient stock in individual *Shorea robusta* Gaertn. f. tree of the Sal forests of Bangladesh

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ABSTRACT

Accurate tree biomass estimation is critical and crucial for calculating carbon stocking as well as for studying climate change, forest health, productivity, nutrient cycling and budget etc. A total of 50 individuals of *Shorea robusta* Gaertn. f. were harvested to assess the biomass of tree components (leaf, branch, bark and stem). Carbon and nutrients (N, P and K) content in the tree components were also measured. This study adopted component biomass models with cross-validation technique. Additive biomass models were developed following the modified Gaussian maximum likelihood aggregated approach using open source software R (version 4.0.1). Component and additive biomass model used D (Diameter at Breast Height) as a sole predictor performed satisfactorily, the inclusion of total tree height (H) in $D^a \cdot H^b$ form showed its supremacy over all the models. The best fitted additive model ($AGB = 0.002056 \cdot D^{2.923998} \cdot H^{-0.69278} + 0.00848 \cdot D^{2.3896} \cdot H^{0.29648} + 0.04224 \cdot D^{2.06986} \cdot H^{0.65549} + 0.00552 \cdot D^{2.06723} \cdot H^{0.70536}$) and conventional model ($\ln(AGB) = -2.7977 + 2.1829 \cdot \ln(D) + 0.5073 \cdot \ln(H)$) took the lowest AIC, MPE and MAE and the highest model efficiency values. The derived species-specific additive and non-additive model showed its superiority over the frequently used pan-tropical models and suggested using this model for estimating aboveground biomass of *S. robusta* in Bangladesh.

1. Introduction

Global climate change chiefly triggered by the dramatic increase in atmospheric carbon and the role played by mainly trees in capturing and storing carbon for a long period of time in the plant biomass draw considerable attention in the recent past especially after the Kyoto Protocol. Kyoto Protocol explicitly considered afforestation, reforestation and regeneration of forests intending to reduce greenhouse gas emissions and partly offset deforestation (IPCC, 2007). Assessment of aboveground biomass (AGB) is central to assessments of forest state and change because of its relationship with carbon dynamics and ecosystem services (Ketterings et al., 2001; Burt et al., 2020) and is a paramount step towards the implementation of the emerging carbon credit market

mechanisms like reducing emissions from deforestation and degradation (REDD+), as they require precise temporal and spatial carbon stock assessment (Yatskov et al., 2019). Besides, it also helps to understand forest health, forest productivity, bioenergy (fuel), nutrient cycling, etc. which ultimately helps to ensure sustainable management of forest and enhance forest carbon stocking (IPCC, 2007).

Tree biomass estimation can be done either by direct or indirect methods. The former is unquestionably known as the most precise approach but requires destructive sampling which is complicated, labor-intensive, and costly (Ketterings et al., 2001; Dong et al., 2015). However, recent mechanized harvesting provides some ease in destructive biomass estimation. Indirect biomass estimation by satellite data, aerial image and numerical altitude models have recently been explored but

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are not always reliable due to some technological limitations such as image acquisition process, data processing techniques, mixed pixels, data saturation, instrument resolution and the scale, selection of suitable algorithms for information extraction, ecological process on the ground (Friedl et al., 2001; Kim et al., 2018). Hence, indirect biomass estimation by allometric model development, i.e. regressing the biomass to some predictor variables, is still considered a better and reliable approach. Though the approach requires initial extensive biomass destruction, it becomes non-destructive once the model was developed and allows large-area studies with repetition (Dimobe et al., 2018).

Allometric biomass estimation can be linear, logarithmic, exponential or power-law (Mensah et al., 2016). The power-law relationship however remains the most common as it supports growth assuming a constant scaling rate across ontogenies (Mensah et al., 2017). The logarithmic transformation of the power function is frequently used by many researchers (Mahmood et al., 2015; Dimobe et al., 2018; Ouédraogo et al., 2020) as it uniformly depicts the relative variation in the relationship between variables, ensures homoscedasticity by stretching small values of variables and compressing for large ones, normalize sample variance and reduce the influence of outliers (Kerkhoff and Enquist, 2009).

Biomass models generally used tree diameter at breast height (D) either alone or in combination with other tree attributes as explanatory variables (Ketterings et al., 2001; Dong et al., 2015; Affleck and Diéguez-Aranda, 2016). As D has lenience in measurement and often accounts for the largest share of variation in tree biomass (Affleck and Diéguez-Aranda, 2016), it is preferred for biomass modeling alone. However, many researchers stated that the inclusion of total tree height (H) has the capacity to improve model accuracy of individual tree biomass estimation greatly (Chave et al., 2005; Mahmood et al., 2020). Chave et al. (2005) showed that H inclusion can reduce error from 19.5% to 12.8% for stand level biomass across all forms of tropical forests. Though other variables can also be used to describe AGB (Bi et al., 2010), they are rarely used in practice as they are much more difficult to obtain in practice (Dong et al., 2018).

Scientific interests in partitioned biomass of tree led to developing component-wise biomass equation (Sanquetta et al., 2015) which afterward were added to get the total AGB (Antonio et al., 2007) ignoring the intrinsic correlations among biomass components (Dong et al., 2015). As a result, the biomass models lack efficiency and additivity (Parresol, 2001), i.e. the sum of predicted component biomass does not add up to the predicted total biomass. Several methods are available to ensure additivity like simple component summation (Parresol, 2001), FIA-CRM (Poudel and Temesgen, 2016), linear and nonlinear seemingly unrelated regression (Parresol, 2001), error-invariable modeling (Dong et al., 2015) and compositional data analysis (Poudel and Temesgen, 2016). Additive models are scarce in use as it requires statistical analysis and software beyond least square regression though it has several merits (Parresol, 2001; Zhang et al., 2016; Fu et al., 2017).

Additive methods can be divided into aggregative and disaggregative approaches (Dong et al., 2015). Both of these approaches were modified later by Affleck and Diéguez-Aranda (2016) to provide valid probabilistic models within the framework of maximum-likelihood. It is considered as an alternative of the method proposed by Parresol (2001). As of now, no best method for additive biomass functions has yet emerged (Vonderach et al., 2018), we wish to develop models following aggregated approach of Affleck and Diéguez-Aranda (2016) as it can be done using open-source political software though it yielded a bit higher standard error.

The tropical moist deciduous Sal forest (Champion et al., 1965) is one of the most economically and ecologically significant forest types especially in the central part of Bangladesh and hence is considered as a leading concession forest (Islam et al., 2015). Unfortunately, two-third of the forest has been encroached in last two decades (FD, 2015). *Shorea robusta* Gaertn. f. is the dominant species (90%) of this forest type either in a pure or mixed form (Kibriya et al., 2019). It is a semi-deciduous species

with high timber value and generally found in the form of coppice forest. Though several biomass models exist for *S. robusta* (e.g. Giri et al., 1999; Behera and Misra, 2006; Patel and Majumdar, 2010; Thapa-Magar and Shrestha, 2015; Banik et al., 2018), no model is developed for this region except a multispecies specific model by Mahmood et al. (2019). However, sometimes multi-species specific models failed to meet the required accuracy (Vahedi et al., 2014). Moreover, they lack information on biomass allocation and nutrient partitioning in biomass though it helps to select and manage trees for augmented production and efficient nutrient cycling in forest ecosystems (Dossa et al., 2008). Furthermore, carbon (C), nitrogen (N) and phosphorus (P) are considered as the most limiting nutrients for C sequestration in an ecosystem (Tang et al., 2018) and K is highly mobile and plays a vital role in performing physiological functions (Marschner, 1995). In addition, researchers are now giving importance to individual carbon content analysis as using default (50%) value may lead to biases of the global vegetation C stock (Ma et al., 2018). Therefore, the present study aims to investigate (1) diameter and height relationship (2) biomass allocations among the tree components (3) derive additive and conventional biomass models for the tree components and total above-ground biomass (4) carbon and nutrient (N, P and K) and (5) compare the derived total above-ground biomass model with the frequently used pantropical, regional models.

2. Materials and methods

2.1. Description of the study site and species

The sample trees were collected from the *S. robusta* natural forest of Rajabari and Gosinga Union of Sreepur Upazila and Mirzapur Union of Gazipur Sadar Upazila of Gazipur District between 24°6" to 24°12" North and 90°26" to 90°30" East Longitude (Fig. 1). This natural forest is dominated by naturally occurring Sal (*Shorea robusta*) trees. It is a protected forest and can be characterized as deciduous types managed by the Forest Department of Bangladesh. The dominated patch of *S. robusta* usually covers 75% of the upper canopy (Alam, 1995; BFD, 2017). *Terminalia belerica*, *Dillenia pentagyna*, *Careya arborea*, *Albizia procera*, *Milius avelutera* and *Lagerstroemia parviflora* are also found in this forest. This forest found to grow in the relatively raised land (45 m above the Mean Sea Level) of Madhupur and Barind tracts (is the largest Pleistocene era pysiographic unit in Bangladesh) (Jahan and Ahmed, 1997; BFD, 2017). The soils are nutrient-poor, acidic (pH, 5.00–5.92) (Alam, 1995), highly oxidized and reddish brown in color. The range of soil moisture content, organic matter is CEC are 5 to 24%, 1.36 to 1.80% and 10.60 to 12.04 me/100 g respectively (Hoque et al., 2008). Mean annual precipitation found to vary from 2000 to 2300 mm and the average maximum and minimum temperatures were 27.5 °C and 18.5 °C respectively.

Shorea robusta is a deciduous tree with an elongated crown at a young age and becomes more rounded as the tree ages. The diameter range of this species falls within 5–65 cm and the height of mature *S. robusta* forest rarely exceeds 30 m (Rahman and Vacik, 2010.) The stem is usually clean, straight and cylindrical. It is a slow growing species. The bark is rough, dark brown and thick with longitudinal fissures deep in poles becoming shallow in mature trees. The leaves are oval, leathery and taper to the tip with a rounded. Small, yellowish-white flowers are arranged in large terminal or axillary racemose panicles. Fruits are oval, hairy and winged comprising oval seed (Tewari, 1995).

2.2. Biomass sampling for fresh and dry weight determination

Fifty individual trees of *S. robusta* having a D range of 5–38 cm were considered as samples. The D range was divided into seven classes as 5–10, 10–15, 15–20, 20–25, 25–30, 30–35 and above. No of individuals were 5, 18, 10, 9, 4, 2 and 1 respectively which was selected before harvesting after conducting a reconnaissance survey to represent the total population of the studied area. The sample trees of each diameter class were selected based on the frequency distribution. Individual trees were

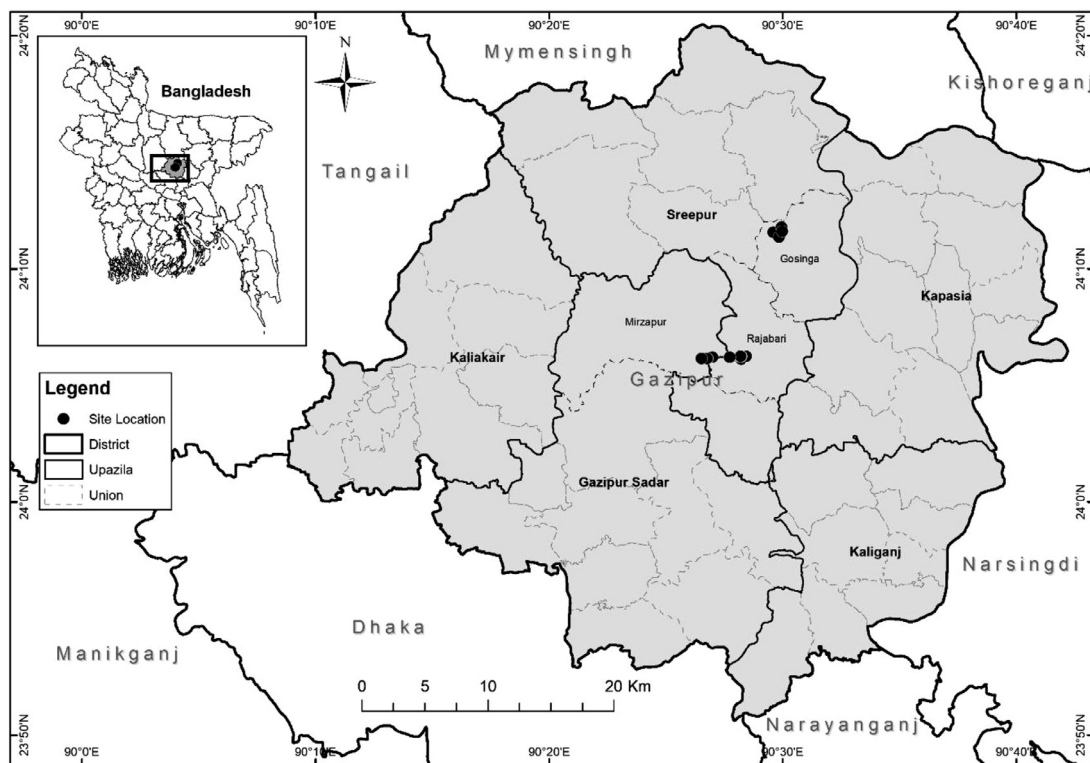


Fig. 1. Location map of the study area.

selected after visualization to avoid mechanically and insect-damaged tree or tree with disease infestation. Prior to harvesting, biometric variables like D, stump diameter (SD) and total height (H) were measured for all individuals, where D and SD were measured using a diameter tape graduated in cm and H was measured by using Criterion RD 1000 (Laser Technology Inc., USA) respectively.

The selected trees were cut at the ground level. The branches were separated from the main trunk and the leaves from the branches. Smaller branches (diameter < 7 cm) were again separated from the bigger branches (diameter > 7 cm). All components were weighed (fresh weight) in the field using a 100 kg balance scale and recorded. One 0.5 m long section was taken from the base of the main stem and bigger branches and 1 m long section was taken from the rest portions. Then it was debarked to obtain fresh bark to fresh stem weight ratio (Mahmood et al., 2012, 2016). Every fifth sample tree was chosen to determine the moisture content of the tree. Sub-samples were taken from the base, middle and top portion for main stem and bigger branch weighing approximately 0.5 kg except for leaves, bark and small stem which were taken randomly with an approximate weight of 0.25 kg. These sub-samples were weighed on a 5 kg balance scale and then brought back to the laboratory where they were oven-dried to a constant weight at 80 °C (Allen, 1989). The dry weight was recorded immediately after removing from the oven and was used to get the conversion ratio of fresh to oven-dry weight for each respective part of the tree. Oven dry weight (biomass) was computed by multiplying the fresh weight with the conversion ratio of the respective tree component.

2.3. Biomass model development and validation

Biomass data were checked for outliers in scatter plots that also assisted in assessing the relationship between the above-ground biomass (AGB) and independent variables (D and H). As the power-law model outperformed linear, logarithmic and exponential model, we developed biomass models for each of the tree components (leaf, branch bark and

stem) following linearized form of power-law model involving D alone, H alone and a combination of D and H (Chave et al., 2005) as follows:

$$\ln(Y) = \ln(\alpha) + \beta \ln(D) \quad (1)$$

$$\ln(Y) = \ln(\alpha) + \beta \ln(D^2H) \quad (2)$$

$$\ln(Y) = \ln(\alpha) + \beta \ln(D) + \gamma \ln(H) \quad (3)$$

Where, Y is the biomass of tree components (Leaf, Branch, Bark and Stem) being modeled. We also developed a model for the estimation of aboveground biomass by using the above predictors in the said form. Combined D and H were used to account for the variation of height for the same value of diameter while solving the collinearity issue in linear regression (Dimobe et al., 2018). We use natural logarithm as it helped to normalize the response variable and thus to meet the prerequisites of linear regression for simple parameter estimation (Dimobe et al., 2018). However, as logarithmic transformation induce a systematic bias, we applied CF (Baskerville, 1972):

$$CF = \exp(RSE^2/2) \quad (4)$$

Where RSE is the residual standard error of the regression model.

Usually, a 5-fold or 10 fold validation is enough to provide a good balance between bias and variance (Sileshi, 2014). Consequently, a 10 fold cross-validation was employed for the evaluation of the predictive model performance of the three selected models. Normality and homoscedasticity of the residuals were tested using Shapiro-Wilks normality and Breusch-Pagan tests, respectively. Fitted models performance was evaluated after back transforming the values of adjusted determination coefficient (R^2), residual standard error (RSE), root mean squared error (RMSE) and mean absolute error (MAE) into the original scale and considering the value.

Biomass allocation to plant components (leaf, branch, bark and stem) was obtained by component-wise biomass fractions (ratio of component biomass and AGB) calculation. For each component biomass, a bivariate relationship between biomass fractions and tree diameter was patterned.

The sample trees were collected only from the *S. robusta* natural forest of the central part of Bangladesh, which contains the lion share of this forest type in Bangladesh. The rest of the fraction is located in the northern part, but inherent the almost similar soil (BFD, 2017). Therefore, it was believed that the derived allometric biomass model may capable to represent the *S. robusta* trees of Bangladesh.

2.4. Additive biomass equations

The additive biomass equation was developed for Eqs. (5)–(7) separately using 40 individually selected random samples following the Gaussian maximum likelihood approach as modified by Affleck and Diéguez-Aranda (2016) as described in the following formulas:

$$\begin{aligned} Y_1 &= \exp^{\beta_{10}} D^{\beta_{11}} + \varepsilon_1 \\ Y_2 &= \exp^{\beta_{20}} D^{\beta_{21}} + \varepsilon_2 \\ Y_3 &= \exp^{\beta_{30}} D^{\beta_{31}} + \varepsilon_3 \\ Y_4 &= \exp^{\beta_{10}} D^{\beta_{11}} + \exp^{\beta_{20}} D^{\beta_{21}} + \exp^{\beta_{30}} D^{\beta_{31}} + \varepsilon_4 \end{aligned} \quad (5)$$

$$\begin{aligned} Y_1 &= \exp^{\beta_{10}} (D^2 H)^{\beta_{11}} + \varepsilon_1 \\ Y_2 &= \exp^{\beta_{20}} (D^2 H)^{\beta_{21}} + \varepsilon_2 \\ Y_3 &= \exp^{\beta_{30}} (D^2 H)^{\beta_{31}} + \varepsilon_3 \\ Y_4 &= \exp^{\beta_{10}} (D^2 H)^{\beta_{11}} + \exp^{\beta_{20}} (D^2 H)^{\beta_{21}} + \exp^{\beta_{30}} (D^2 H)^{\beta_{31}} + \varepsilon_4 \end{aligned} \quad (6)$$

and

$$\begin{aligned} Y_1 &= \exp^{\beta_{10}} D^{\beta_{11}} H^{\beta_{12}} + \varepsilon_1 \\ Y_2 &= \exp^{\beta_{20}} D^{\beta_{21}} H^{\beta_{22}} + \varepsilon_2 \\ Y_3 &= \exp^{\beta_{30}} D^{\beta_{31}} H^{\beta_{32}} + \varepsilon_3 \\ Y_4 &= \exp^{\beta_{10}} D^{\beta_{11}} H^{\beta_{12}} + \exp^{\beta_{20}} D^{\beta_{21}} H^{\beta_{22}} + \exp^{\beta_{30}} D^{\beta_{31}} H^{\beta_{32}} + \varepsilon_4 \end{aligned} \quad (7)$$

Where, Y_1 to Y_3 implies the component (leaves, branches and stem) and Y_4 indicates the total above-ground biomass (kg); β_{ij} denotes the regression coefficients. Here, the errors are intrinsically correlated for an individual tree and can be expressed as $\varepsilon = [\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4]$ assuming ε equals to 0 and the variance and covariance matrix ($\varepsilon\varepsilon'$) will be sum total (Σ). The cross equation restrictions on the structural parameters compel each coefficient to be shared between two equations. All models were fitted simultaneously using joint-generalized least squares (also recognized as NSUR) under the restriction of coefficients to ensure additive.

Ten sample trees were selected for model evaluation from five diameter classes. The number of samples was 2, 3, 3, 1 and 1 for the diameter class of 5–10, 10–15, 15–20, 20–25 and 25–30 respectively. These sample trees were used for goodness-of-fit statistics: Akaike information criterion (AIC), adjusted coefficient of determination (adjusted R^2), mean absolute error (MAE) and root mean square error (RMSE) (Soares and Schaeffer-Novelli, 2005; Siddique et al., 2012; Mahmood et al., 2016). The equation with the lowest AIC, RMSE and MAE and the highest adjusted R^2 was considered as the best. Residual distribution homogeneity and bias were checked visually by residual plots with loess regression lines overlaid on the plots. Finally, a paired t -test was carried out to validate the additive model by comparing the fitted values with the observed values. Underestimation or overestimation was explored by creating a 1:1 line (ideal model) graphically by putting observed values in the y-axis against fitted values on the x-axis as recommended by Sileshi (2014). The alpha level was always kept at 0.05 for statistical analysis.

2.5. Performance of the additive model

Our best-fitted additive and non-additive models were compared with the following commonly used pan-tropical generic models developed by Brown (1997), Nelson et al. (1999), Chave et al. (2005, 2014), Brown et al. (1989), Djomo et al. (2010), Giri et al. (1999) and Mahmood et al. (2019) for broadly defined forest types. Here, we used the wood density of Sattar et al. (1999) in comparing these models. The appropriateness was determined by comparing the adjusted R^2 ,

Model Prediction error (MPE), bias (%) and mean absolute percent error (MAPE).

2.6. Estimation of carbon and nutrient (N, P and K) content

A total of six individual tree (i.e. one harvested individual from each diameter class) was selected. Three replicates of each component of an individual (18 sample for a components) were taken for the determination of carbon, nitrogen, phosphorus and potassium. The oven-dried samples were crushed, processed and acid digested according to Allen (1989). Carbon (C) content was determined by ash method (Dimobe et al., 2018). Nitrogen (N) content were determined according to Baethgen and Alley (1989) while Phosphorus (P) was determined according to Murphy and Riley (1962), respectively using UV-Visible Recording Spectrophotometer (HITACHI U-2910, Japan). Potassium content was measured in sample extracts by Flame photometer (PFP7, Jenway LTD, England).

3. Result

3.1. Diameter and height relationship

The D showed a strong relationship with H and stump diameter having the values as given in the table (Table 1). The performance was evaluated after back transforming the values into the original scale.

3.2. Biomass partitioning

Biomass allocations to four different components were $72.93 \pm 4.33\%$, $14.89 \pm 4.7\%$, $10.71 \pm 0.58\%$ and $1.47 \pm 0.59\%$ for the stem, branch, bark and leaf respectively. The biomass proportion of stem decreased with increasing diameter whereas the other components (branch, bark and leaf) showed an opposite relationship with increasing diameter (Fig. 2). The results suggest that as the tree size increases, more biomass is allocated to foliage rather than to the woody structure.

3.3. Carbon and nutrients (N, P and K) in tree components

Comparatively higher concentration (57.02%) of carbon was observed in stem followed by branches. While, higher N (1.75%), P (0.13%) and K (0.73%) concentrations were observed in leaves and very lower concentration these nutrients was observed for stem and bigger branches (Table 2).

3.4. Biomass additive systems

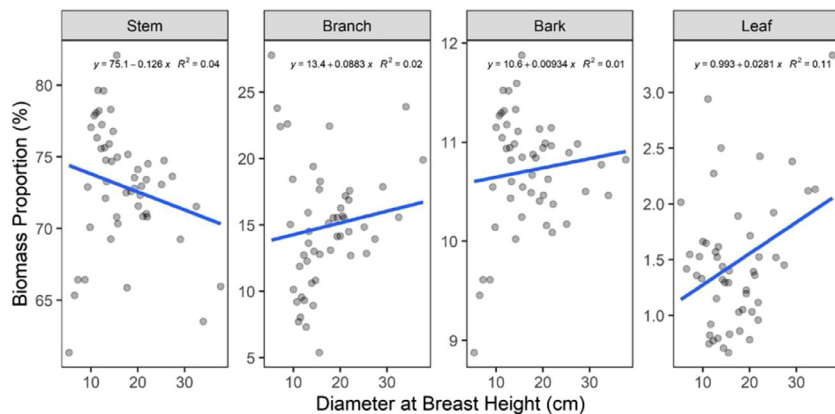
A nonlinear trend was observed for the biomass of leaf, branch, bark and stem concerning D and H as displayed in Fig. 3. Each of the component models performed well with an adjusted R^2 value range from 0.6969 to 0.9897 with highly significant model coefficients ($p < 0.001$). However, the stem biomass showed the highest fitness values (adj. $R^2 > 0.9636$ –0.9839 for all the model forms), whereas the adjusted R^2 values for leaf, branch and bark were in between 0.6969–0.8967, 0.8549–0.9 and 0.98–0.9897 respectively. Interestingly, the inclusion of H in any form did not always increase the accuracy of biomass predictions (Table 3). It is also found that D alone yielded a reliable prediction of biomass for tree components but the models with D and H as independent variable showed better performance for all the tree components and AGB considering the value of the adjusted R^2 , RMSE, RSE and MAE. The best fit conventional AGB model was $\ln(\text{AGB}) = -2.7977 + 2.1829 \ln(D) + 0.5073 \ln(H)$ (Table 3).

The three additive models (Models 1–3) showed an insignificant difference between the predicted and observed total above-ground biomass values (paired t -test, $p > 0.05$). Though all the additive equations showed higher model efficiency value (0.9669–0.9878), which were very close to the reference value 1. However, the model 3

Table 1

Regression coefficients with goodness-of-fit statistics of height-diameter and stump diameter-diameter equation.

Model	Regression Coefficients		CF	Evaluation Statistics			
	a (SE)	b (SE)		Adj. R ²	RSE	RMSE	MAE
$\ln(H) \sim a + b \ln(D)$	0.6666 (0.1324)	0.6398 (0.0477)	1.0098	0.7292	1.5349	0.0193	1.1753
$\ln(SD) \sim a + b \ln(D)$	0.6575 (0.0633)	0.83684 (0.0228)	1.0022	0.9728	1.2243	0.0092	0.9972

**Fig. 2.** Relationship of the component mass fraction with DBH.**Table 2**Average concentration of C, N, P and K in different components of *Shorea robusta* Gaertn. f.

Plant Component	Carbon (%) (SE)	Nitrogen (%) (SE)	Phosphorus (%) (SE)	Potassium (%) (SE)
Stem	48.24 (0.34)	0.52 (0.07)	0.001 (0.00)	0.15 (0.01)
Branch	46.90 (0.48)	0.61 (0.06)	0.01 (0.00)	0.14 (0.02)
Bark	47.85 (1.23)	0.45 (0.13)	0.01 (0.00)	0.24 (0.02)
Leaf	45.74 (0.57)	1.75 (0.17)	0.13 (0.01)	0.73 (0.03)

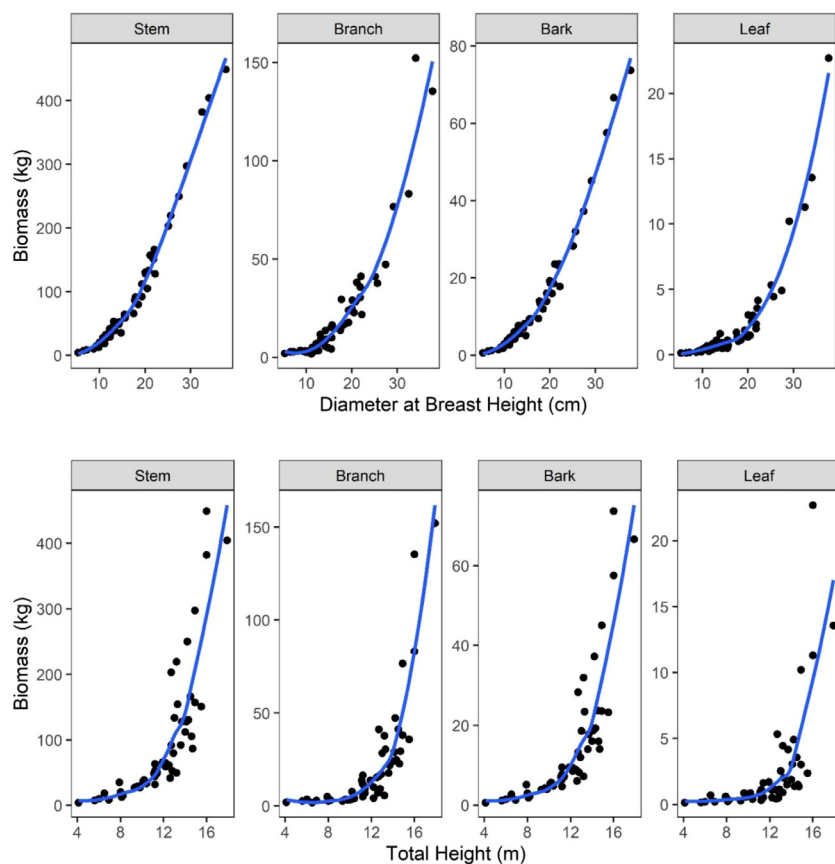
**Fig. 3.** Relationship between leaf, branch, stem biomass and diameter at breast height (dbh) and total height (h) respectively.

Table 3

Regression coefficients with goodness-of-fit statistics of the component-wise biomass and total aboveground biomass allometric equations.

Model	Component	Regression Coefficients			CF	Evaluation Statistics			
		a (SE)	b (SE)	c (SE)		Adj. R ²	RSE	RMSE	MAE
ln (B) ~ a + b ln (D)	AGB	-2.4595 (0.1559)	2.5075 (0.0561)		1.01349	0.9815	20.6254	0.02269	12.5772
ln (B) ~ a + b ln (D ² H)		-3.0387 (0.1647)	0.9431 (0.0206)		1.01287	0.9733	24.7804	0.02215	15.7793
ln (B) ~ a + b ln (D) + c ln (H)	Stem	-2.7977 (0.1757)	2.1829 (0.1115)	0.5073 (0.155)	1.0112	0.9867	17.5244	0.02047	12.0934
ln (B) ~ a + b ln (D)		-2.7697 (0.1498)	2.5049 (0.0539)		1.01245	0.9636	19.5325	0.0218	9.4128
ln (B) ~ a + b ln (D ² H)	Branch	-3.3653 (0.1399)	0.9442 (0.0175)		1.0093	0.9801	14.428	0.0188	9.2573
ln (B) ~ a + b ln (D) + c ln (H)		-3.1999 (0.1537)	2.092 (0.0975)	0.64537 (0.1355)	1.0086	0.9839	12.9974	0.0179	8.8728
ln (B) ~ a + b ln (D)	Bark	-4.5684 (0.4007)	2.563 (0.1442)		1.0926	0.9899	9.6368	0.0583	4.7992
ln (B) ~ a + b ln (D ² H)		-5.1008 (0.4536)	0.9564 (0.0567)		1.1019	0.8549	11.6024	0.06104	5.5059
ln (B) ~ a + b ln (D) + c ln (H)	Leaf	-4.5882 (0.5005)	2.544 (0.3178)	0.02972 (0.4414)	1.0947	0.9000	9.6322	0.0583	4.7943
ln (B) ~ a + b ln (D)		-4.7951 (0.1499)	2.544 (0.0539)		1.0125	0.9800	2.2825	0.0218	1.2742
ln (B) ~ a + b ln (D ² H)		-5.4000 (0.1392)	0.959 (0.0174)		1.0092	0.9814	2.2051	0.0187	1.4032
ln (B) ~ a + b ln (D) + c ln (H)		-5.2324 (0.1526)	2.1243 (0.0969)	0.65598 (0.1346)	1.0084	0.9897	1.6397	0.0178	1.0981
ln (B) ~ a + b ln (D)		-7.171 (0.3591)	2.66 (0.1292)		1.0737	0.815	1.7219	0.0523	0.7286
ln (B) ~ a + b ln (D ² H)		-7.5922 (0.4621)	0.9761 (0.0578)		1.1059	0.6969	2.2039	0.0621	0.9031
ln (B) ~ a + b ln (D) + c ln (H)		-6.4742 (0.4139)	3.3287 (0.2627)	-1.0452 (0.3650)	1.0638	0.8967	1.2869	0.0482	0.6126

Table 4

Coefficients with standard error (SE) and goodness-of-fit statistics of the additive allometric equations.

Model	Regression Coefficients												Evaluation Statistics				
	Leaf			Branch			Stem/bole			Bark			Model Efficiency	AIC	RMSE	MAE	MPE
	a (SE)	b (SE)	c (SE)	a (SE)	b (SE)	c (SE)	a (SE)	b (SE)	c (SE)	a (SE)	b (SE)	c (SE)					
Eq. (5)	0.0005674 (0.00026)	2.776539 (0.1613)		0.009249 (0.0035)	2.61822 (0.1241)		0.05879 (0.0087)	2.53365 (0.0568)		0.00818 (0.0012)	2.55238 (0.0572)		0.9669	78.551	2.0893	24.067	1.288
Eq. (6)	0.00126 (0.000598)	0.854748 (0.0628)		0.00387 (0.0018)	1.01447 (0.0546)		0.03726 (0.006)	0.93263 (0.0207)		0.004851 (0.00078)	0.94771 (0.0205)		0.9673	81.762	11.304	28.184	1.368
Eq. (7)	0.002056 (0.00076)	2.923998 (0.3138)	-0.69278 (0.3918)	0.00848 (0.0059)	2.3896 (0.2395)	0.29648 (0.4512)	0.04224 (0.0073)	2.06986 (0.1239)	0.65549 (0.1599)	0.00552 (0.00099)	2.06723 (0.1198)	0.70536 (0.1595)	0.9878	71.912	6.558	17.707	0.836

[$B = 0.002056 \cdot D^{2.923998} \cdot H^{-0.69278} + 0.00848 \cdot D^{2.3896} \cdot H^{0.29648} + 0.04224 \cdot D^{2.06986} \cdot H^{0.65549} + 0.00552 \cdot D^{2.06723} \cdot H^{0.70536}$] yielded the highest efficiency value (0.9878) with the lowest AIC (71.912), MAE (17.707) and MPE (0.836) values. Model 2 is a very close competitor of model 1 with respect to AIC, MAE and MPE values though it expressed its superiority with the least RMSE (2.0893) value among the three models (Table 4). The best model (Model 3) yielded the component-wise regression line, which were close to the 1:1 line (Fig. 4).

3.5. Performance of the developed additive model

The derived conventional biomass models showed the best performance over the frequently used pan-tropical and regional models considering the model efficiency (0.989), MPE (0.647) and bias% (5.493) (Table 5). On the other hand, the derived additive AGB model also showed similar model efficiency (0.988) with the least MAPE (9.841) value. The models developed by Giri et al. (1999) and Brown et al. (1989) proved to be a close competitor of our derived conventional and additive AGB models (Table 5).

4. Discussion

The importance of biomass allocation study was discussed by several scholars recently (e.g. Dong et al., 2015; Widagdo et al., 2020). In our present study, biomass allocation varied among the tree components (Mensah et al., 2016). The stem biomass had the lion's share in total aboveground biomass (60–80%) while leaf biomass has the least contribution (2–3%). Similar results were obtained for mangroves by Ong et al. (2004) and Sherman et al. (2003). Resource partitioning among plant components is a part of a plant's strategy built as a response to plant competition and as a tree grows. In a natural environment, the

foliage biomass increases with both tree size and stocking until it is constrained by canopy closure (Bi et al., 2010). The increasing pattern of foliage biomass with increasing tree diameter implies the openness of the natural forest (Subedi et al., 2012), which provides chances to harvest better light. Again, the retention of higher branches and foliage may also be affected by the over story variables as stated by Naidu et al. (1998). Comparatively, poor goodness of fit statistics was observed for the leaves and branches while the best was observed for stem and bark. However, the presented equations for estimating the biomass of individual plant components are quite satisfactory as the biomass of leaves and branches is more influenced by internal and external factors (Sanquetta et al., 2015).

As significant differences exist in energy, carbon and nutrient concentration among the plant's biomass components (Zhao et al., 2014), accurate estimation is crucial to understand carbon accounting, nutrient budgeting, maintaining forest productivity (Mahmood et al., 2019) and predicting impact of global change on C cycling (Tian et al., 2015). Moreover, exploring nutrients content across plant components is considered as a way to reveal the allocation strategies of nutrients for tree species (Yan et al., 2016). We found that differences are evident in carbon and nutrient concentrations among the tree components. Nutrient uptake and its storage vary with species, stage of plant growth and productive capacity of the site (Mahmood et al., 2019). Moreover, the variation in carbon and nutrient concentrations may also be attributed to the structural component of the plant cell (Kaakinen et al., 2004), functions performed (Kerkhoff et al., 2006), the physiological age of the plant tissue, the position of the tissue in plant, available form of the nutrients in the substrate, concentration of other nutrients, climatic and soil factors (Mahmood et al., 2004). As leaves perform physiological functions, plants tend to allocate higher concentrations of nutrients than structural components to support the plant's survival and productivity

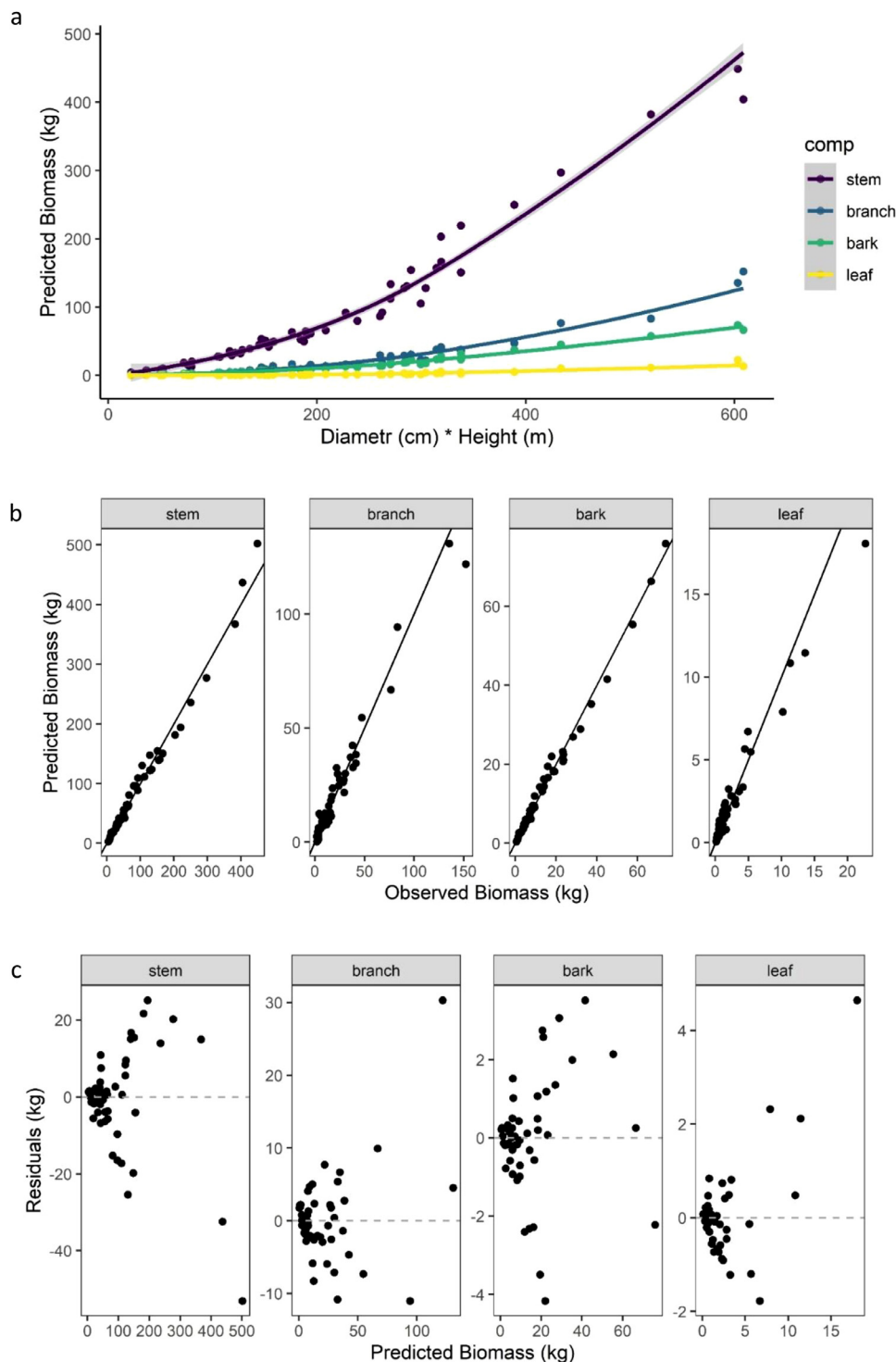


Fig. 4. (a) Component-wise relationship with diameter at breast height (DBH) (b) Component-wise scatterplots of the observed (x-axis) and the predicted (y-axis) biomass values of the best fit model. The black line denotes 1:1 equivalence, (c) component-wise residual vs fitted line of the best fit models.

(He et al., 2016). On the contrary, the structural components require less amount of nutrients as their main functions are to support, absorb and transport. In addition, nutrient contents in stem and branch can be diluted by the metabolically inactive, carbon-rich and nutrient-poor support structure of woody tissue (Kerkhoff et al., 2006). The nutrient contents were similar with the finding of Gautam et al. (2011) for *S. robusta* in India. Moreover, the carbon content of plant components varied with components and was found below (45.74–48.24%) the default value which is in between the range observed by Ma et al. (2018) while doing global synthesis. However, the carbon and nutrient concentration in tree components can be multiplied with the component wise biomass

(derived from the best fit model) to accurate estimation of their stock instead of using average concentration for the plant (Mahmood et al., 2019).

Accurate biomass models are key to estimate carbon stocks from forest inventories and provide comparable and verifiable information to policymakers and stakeholders (Risio et al., 2014). As a result, biomass equations are frequent in ecological and forestry studies over the last 60 years (Bi et al., 2015). Biomass models are getting preferences as it becomes non-destructive after initial destruction and the recent mechanized harvesting reduces some of the previous complexities and cost. Among the available models, the power-law equation proved its

Table 5

Comparison with some existing common biomass equations usually used for mangroves biomass estimation.

Source Model	Predictor	Model Efficiency	MPE	Bias	MAPE
(Brown, 1997) moist	D	0.22321	5.584217	−53.8233	56.24607
(Nelson et al., 1999)	D, H and WD	0.895997	2.043309	−21.7805	32.27386
(Chave et al., 2005)	D, H and WD	0.915897	1.83745	−18.1721	17.64839
(Chave et al., 2014)	D, H and WD	0.856196	2.402684	−25.584	28.25141
(Brown et al., 1989) moist	D and H	0.976201	0.977448	−9.90503	12.73389
(Djomo et al., 2010)	D and H	0.944231	1.496259	−14.9701	15.85872
(Giri et al., 1999)	D and H	0.970628	1.085875	−10.0698	10.8953
(Huy et al., 2016)	D	0.12822	10.00371	−69.9184	67.09032
(Mahmood et al., 2019) deciduous	D, H and WD	0.92895	1.688858	17.51069	17.14046
Conventional derived model _AGB_Model	D and H	0.98956	0.647384	5.493397	10.0661
Derived additive model	D and H	0.987815	0.699384	6.557648	9.841151

superiority in terms of biomass estimation accuracy (Dong et al., 2018). The logarithmic transformation showed its capacity to predict biomass with great accuracy as it complies with the conditions of normality and homoscedasticity (Chave et al., 2005). The explained variance of the fitted models at stem, branch and bark ranged from 85.49–98.97% with the exception for the leaf as also reported by Mensah et al. (2017) and Ouédraogo et al. (2020) in previous studies.

For the development of biomass models, D is considered as an indispensable predictor of biomass models as it can explain a satisfactory (more than 75%) tree biomass variability and provides ease for application (Dong et al., 2018; Dimobe et al., 2018). Our tree diameter based model provided a satisfactory biomass estimation as it can explain from 81.5–98% of the total variation with low RMSE (not above 0.06). The results indicate that D is a strong sole indicator of aboveground biomass which is similar to the findings of Henry et al. (2011) and Vahedi et al. (2014). This may originate from the intimate co-relation between components and tree diameter (Dong et al., 2020). Adding total tree height with diameter increased the predictive efficiency of the component model a bit as like Fayolle et al. (2018) and therefore it is advised to use the total tree height as an additional predictor to achieve more accuracy which was also suggested by Chave et al. (2005).

Additivity in biomass model is more acceptable as non-additive models cannot synchronously consider the totality of predictions obtained from component-wise equations and the predictions obtained for the entire tree (Parresol, 2001; Dong et al., 2015). Moreover, as it considers the instinctive correlation among plant component biomass, it assures higher statistical efficiency by reducing confidence and prediction intervals in biomass estimation (Parresol, 2001; Zhao et al., 2019). The non-linear model was chosen for this study as it avoids the complex calibration of multicomponent equations (Affleck and Diéguez-Aranda, 2016). The imposed constriction on regression coefficients guarantees the additivity of the SUR method (Huff et al., 2017). In addition, it provides a consistent coefficient to ensure consistency in biomass estimation with minor confidence and prediction limits (Sanquetta et al., 2015; Huff et al., 2017). Among the three additive models, model 3 yielded the best prediction while model 2 yielded the least prediction considering model efficiency, AIC, MAE, RMSE and MPE values. Model 2 is a very close competitor of model 1 with respect to model efficiency, AIC, MAE and MPE values but it showed its superiority over model 2 just by having the lowest RMSE value. Though model 2 (D^2H form) and model 3 (D^*H form) include height as an additional parameter for the biomass model, model 2 is comparatively worse than model 3 which suggests that the form of inclusion demands special attention. We also propose the use of model 1 in addition to Model 3 as it is simple and yielded the lowest RMSE (2.0893) value with an acceptable model efficiency (0.9669), AIC (78.551), MAE (24.067) and MPE (1.288) values.

Comparison with the frequently used biomass models helps to assess the uncertainty and suitability of the derived model (Nam et al., 2016). Among all the models, our best fit conventional and additive AGB models exhibited the higher model efficiency with the lowest prediction error, bias (%) and MAPE. Therefore, we are suggesting to use the derived

best fit conventional and additive AGB models instead of frequently used pantropical generic models. Among the frequently used pan-tropical models, the models of Giri et al. (1999) and Brown et al. (1989) proved to be a close competitor for biomass estimation of *S. robusta*. Many scholars observed that locally developed biomass models generate less uncertainty than the pan-tropical model (e.g. (Maulana et al., 2016) in Indonesia, (Kenzo et al., 2009) in Sarawak, Malaysia, (Alvarez et al., 2012) in Columbia, and (Nam et al., 2016) in Vietnam, (Mahmood et al., 2019) in Village forest and Hill zone of Bangladesh). Khan et al. (2020) derived the allometric model for *S. robusta* to estimate carbon stock in the *S. robusta* forest of Bangladesh. This model was for stand level, which was not able to compare for the individual tree model. Moreover, Khan et al. (2020) estimated carbon stock only for the stem using the non-destructive method, which may underestimate the carbon stock in the *S. robusta* forest. Therefore it can be expected that the derived allometric biomass models of the present study are capable to estimate the biomass, carbon and nutrient stock more accurately compared to the model of Khan et al. (2020).

5. Conclusion

Accurate estimation of biomass, carbon and nutrient stock in a forest stand is vital for understanding for the ecosystem functioning and determining the course of actions for the sustainable management of forests. The derived allometric models showed higher efficiencies in biomass estimation compared to the other frequently used pan-tropical and regional biomass models. The site and species specific allometric biomass models that are derived using the destructive methods are more accurate and reliable tool. It is expected that the derived models can be used to estimate the total aboveground as well as component wise biomass of *S. robusta* trees of the Sal forests of Bangladesh.

Declaration of Competing Interest

None

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