

SEMI-DESTRUCTIVE METHOD TO DERIVE ALLOMETRIC ABOVEGROUND BIOMASS MODEL FOR VILLAGE FOREST OF BANGLADESH: COMPARISON OF REGIONAL AND PAN-TROPICAL MODELS

Mahmood H^{1,*}, Siddique MRH¹, Abdullah SMR¹, Islam SMZ², Matieu H³, Iqbal MZ⁴ & Akhter M⁴

¹Forestry and Wood Technology Discipline, Khulna University, Khulna 9208, Bangladesh

²Forest Inventory Division, Bangladesh Forest Research Institute, Chittagong 4210, Bangladesh

³Food and Agriculture Organization of the United Nations, 00153 Rome, Italy

⁴Bangladesh Forest Department, Dhaka 1222, Bangladesh

*mahmoodhossain@hotmail.com

Submitted May 2019; accepted March 2020

Pan-tropical biomass models were developed for natural and plantation forests, which cover a wide range of geographical areas and tree species. Tree architecture of a species significantly varies among plantations and natural forests as well as village forests or homestead areas. Tree architecture has a significant influence on biomass estimation in allometric models. Therefore, it was hypothesised that pan-tropical biomass models may not be able to address the desired accuracy in biomass estimation for village forests. The objective of this study was to derive a common allometric above-ground biomass model for a village forest in Bangladesh and to compare the efficiency of the derived model with frequently used pan-tropical models. This study adopted a semi-destructive method, where the biomass of individual sampled trees was derived from stem volume, wood density and biomass expansion factor. Eight linear models [natural logarithm (Ln) transformed] were used to derive the best-fit allometric biomass model. In comparison with the best-fit model, the frequently used pan-tropical models showed significant estimation of total above-ground biomass (TAGB). Therefore, the derived model for the village forest showed higher capacity to reduce uncertainty in biomass estimation compared to pan-tropical models. This finding may restrict the indiscriminate use of pan-tropical models without checking their accuracy towards a particular forest type and species.

Keywords: Allometry, biomass expansion factor, inventory, pan-tropical model, village forest

INTRODUCTION

Biomass estimation is important for understanding the productivity, rate of carbon sequestration and cycling of nutrients in a particular forest ecosystem (Mahmood et al. 2008, Mahmood 2014). Nationwide or region wise biomass and carbon stock assessments have important implications in formulating forest policy and management interventions, and preparing the government reports for strategic planning on the use of renewable forest resources (Paladinić et al. 2009). Accurate estimation of carbon stock is badly needed in developing countries to reduce emission from deforestation and forest degradation (REDD+) activities, as well as conservation of carbon stock in their forests. Destructive and non-destructive methods can be adopted to estimate forest biomass (Ketterings et al. 2001). Allometric biomass models are frequently used to estimate

biomass of trees or forests due to their non-destructiveness (Ketterings et al. 2001, Picard et al. 2012). These models can be species specific at local and regional levels, and multi-species at local, regional or biospheric (pan-tropical) scales (Brown et al. 1989, Ketterings et al. 2001, Chave et al. 2005, Chave et al. 2014). The localised species-specific allometric models are quite robust compared to regional or pan-tropical models (Nam et al. 2016). Sometimes, it is an unrealistic expectation to get species-specific allometric models for all the tree species for biomass estimation of a larger area like nationwide or region wise (Brown 1997, Komiyama et al. 2005, Mahmood et al. 2016a). In these cases, a common wood density value, biomass expansion factor (BEF), form factor and stem volume data are used to estimate the biomass stock (FAO 2001, Eggleston et al. 2006, Lisboa et al. 2018). Use of

such method may generate large uncertainty in biomass estimation (Njana 2017). Such situation encourages to use multi-species local, regional or pan-tropical allometric models to estimate tree/forest biomass (Brown et al. 1989, Komiyama et al. 2005, Chave et al. 2014, Nam et al. 2016). The use of multi species pan-tropical/generic allometric biomass models also yield less accurate estimation of tree biomass compared to using species and site specific models (Paul et al. 2013). The pan-tropical models are capable to poorly generalise with its polynomial function that results implausible relationship among biomass, as well as diameter and height of trees (Sileshi 2014). Moreover, they are not able to capture the ecological and/or historical factors that cause unusual properties to trees (Nam et al. 2016, Maulana et al. 2016).

There are 27 allometric biomass models for 11 tree species in Bangladesh, mostly for timber and fuelwood species (Mahmood et al. 2016a). These limited number of biomass allometric models influence the use of pan-tropical models for estimating biomass of smaller and larger areas. The pan-tropical biomass model of Brown et al. (1989) and Chave et al. (2005) were used to estimate the biomass and carbon stock for plantations, natural forest, roadside plantations and village forest/homestead areas of Bangladesh (Miah et al. 2009, Ullah and Al-Amin 2012, Rahman et al. 2015, Jamal et al. 2016). The tree architecture of a species varies with age, site and stand management intervention (Poorter et al. 2003). Consequently, tree biomass is found to vary with tree architecture (Ketterings et al. 2001). Therefore, indiscriminate use of pan-tropical biomass models may produce higher level of uncertainty in the estimation of biomass and carbon stock in different forest types and plantations of Bangladesh. Nevertheless, region/forest type wise multi-species common allometric biomass model may increase the accuracy in biomass estimation compared to the frequently used pan-tropical models (Nam et al. 2014, Maulana et al. 2016). Thus, the present study hypothesised that pan-tropical biomass models may not be able to address the desired accuracy in biomass estimation for village forest in Bangladesh. Therefore, the study aimed i) to derive a multi-species common allometric biomass model for tree species of village forest using semi-destructive method and ii) to test the accuracy of the derived best-fit model compared

with the frequently used pan-tropical biomass models.

MATERIALS AND METHODS

Description of the study area

Village forest includes all trees grown outside the classified forest. It includes wet parts at the south and east, and drier parts at the north west Bangladesh (Figure 1). The village forest contains 109,000 km² of land area, that is about 73.58% of the total land of Bangladesh. This forest plays a vital role in the economic development of the rural household by supplying bulk of wood and other timber products for household consumption and industrial uses. The major tree species of the village forest in Bangladesh are *Albizia* spp. *Aphanamixis polystachya*, *Artocarpus heterophyllus*, *Mangifera indica*, *Lannea coromandelica*, *Swietenia macrophylla* and *Syzygium cumini* (Millate-E-Mustafa et al. 1996, Hasanuzzaman et al. 2014). The mean temperature of the village forest during winter and summer are 17 and 32 °C respectively, while the mean annual rainfall and relative humidity are about 1800 mm and 74.3% respectively (Banglapedia 2014). The studied species of the village forest were *Albizia procera*, *A. richardiana*, *A. saman*, *A. polystachya*, *A. heterophyllus*, *L. coromandelica*, *M. indica*, *S. macrophylla* and *S. cumini*. These species are categorised as timber and fruit trees. *Albizia procera*, *A. richardiana*, *A. saman*, *A. polystachya* and *S. macrophylla* are timber producing species and their pruned branches are used as fuelwood. *Lannea coromandelica* is a medium sized tree mainly used for construction, while, *A. heterophyllus*, *M. indica* and *S. cumini* are medium sized fruit trees which are sometimes used for construction and furniture making (Das & Alam 2001).

Biomass expansion factor (BEF)

Sampling of trees for biomass expansion factor (BEF)

A total of 42 sample trees (6 individuals from each species) of *A. procera*, *A. richardiana*, *A. saman*, *A. heterophyllus*, *M. indica*, *S. macrophylla*, and *S. cumini* was selected from the village forest areas of Bangladesh. The range of diameter at breast height (D) and total height (H) of the

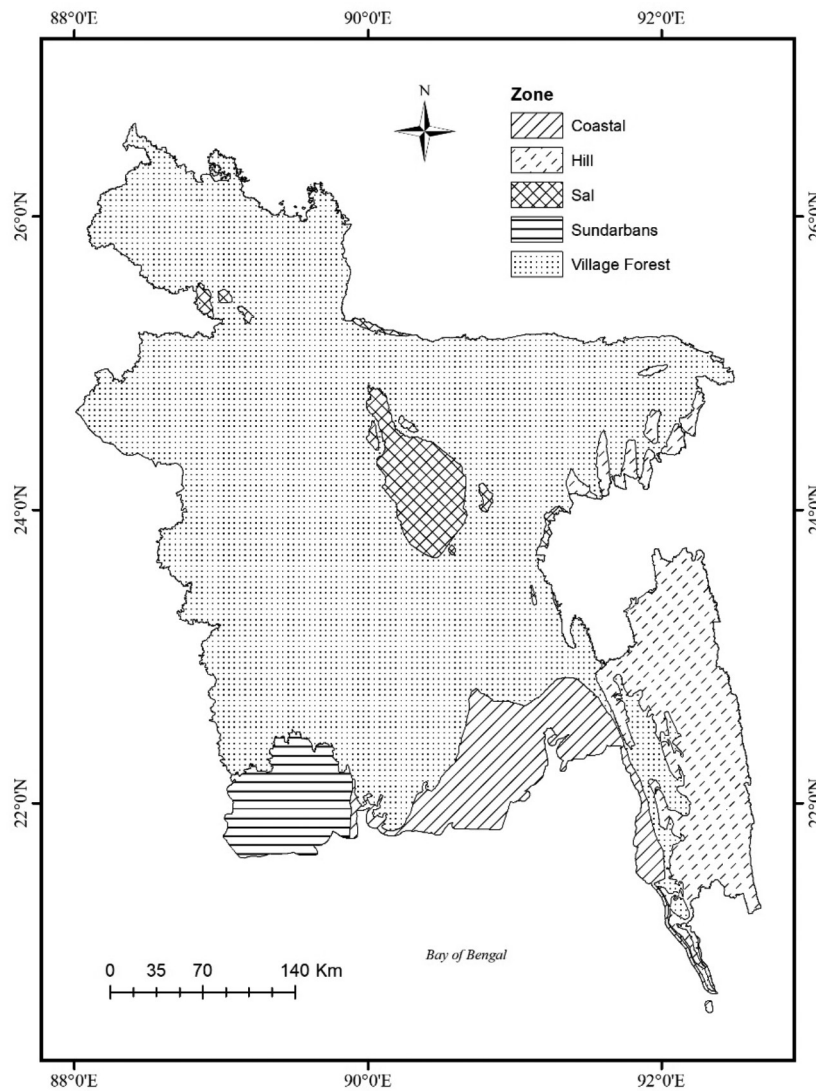


Figure 1 Forest areas of Bangladesh

sampled trees were 8.3 to 83.1 cm and 4.9 to 32.9 m respectively.

Field and laboratory measurement

Species name and D were recorded before felling the sampled trees. The sampled trees were felled at ground level, and the stem linear length of each individual tree was measured and recorded as H. The felled trees were separated into stem, bigger branches (diameter > 7 cm), smaller branches (diameter < 7 cm) and leaves. The fresh weight of each part of the felled tree was measured separately in the field and recorded.

Ten sub-samples (about 250 g) of leaves and smaller branches, and ten disks (2 cm thick) of stem and bigger branches of each species were taken immediately after felling the trees. These

sub-samples were transported to the laboratory and oven-dried at 105 °C for seven days to get the fresh to oven-dry weight conversion ratio for each component of individual species. The fresh weight of each component of the individual sampled tree was multiplied with their respective conversion ratio to get component wise oven-dry biomass. Finally, oven-dry biomass of all components of sampled trees were added to get the total oven-dry above-ground biomass (Mahmood et al. 2016b). The BEF of sampled tree was calculated from the ratio of total above-ground biomass (TAGB) and oven-dry stem biomass (Taeroc et al. 2015).

$$BEF = \frac{\text{Total aboveground biomass}}{\text{Stem biomass}}$$

Models of biomass expansion factor (BEF)

The BEF of trees were found to vary with species, D, H and age (Sanquetta et al. 2011). Instead of constant or average BEF, tree size (D and H) was considered as an independent variable to derive the best-fit BEF model. Ten frequently used BEF models ($BEF = a + b \cdot D$, $BEF = a \cdot \exp(D \cdot b)$, $BEF = a \cdot H^b$, $BEF = a \cdot \exp(H \cdot b)$, $BEF = a \cdot (D \cdot H)^b$, $BEF = a - (D \cdot H)^b$, $BEF = a \cdot (D/H)^b$, $BEF = a \cdot \exp(D/H)^b$, $BEF = \exp(a - D)^b + \exp(c) \cdot D + 1$, and $BEF = \exp(a - D)^b + \exp(c) \cdot D / (H^2 + 1)$) were tried, where D = diameter at breast height, H = total height) (Sanquetta et al. 2011, Longuetaud et al. 2013). The best-fit BEF model was selected by considering the lowest values of Akaike information criterion (AIC) and root mean square error (rmse), and highest value of adjusted R² (Longuetaud et al. 2013). The statistical software R (3.2.3) was used to derive BEF models, and AIC and RMSE values of all models.

Allometric model of stem and total above-ground (TAGB) biomass

Data collection and compilation

This study used stem volume data of 817 individuals of 9 studied tree species of village forest. The mean value with ranges of D, H and wood density (W) of the sampled tree species are presented in Table 1. Bangladesh Forest Research Institute collected the volume data from the village forest areas of Bangladesh and developed

volume tables for those species (Latif and Islam 2000). Stem biomass (kg) of individual sampled trees was estimated from their stem volume (m³) and W (kg m⁻³) value of the respective tree species, as derived by Satter et al. (1999). Finally, the TAGB of individual trees was estimated by multiplying the stem biomass and BEF of the respective individuals obtained from the best-fit BEF model (Soares & Tome 2012).

Allometric model development and model selection

The independent variables (D, H and W) and dependent variables (stem biomass and TAGB) were transformed to natural logarithm (Ln) to improve the linearity and homoscedasticity. The total dataset (817 individuals) was divided into data set A and B. Data set A contained randomly selected 650 individuals, which was used to derive the allometric model. Data set B contained the rest of the individuals to validate the derived best-fit model and comparison. Eight frequently used pan-tropical biomass models were tested to derive the best-fit allometric model for TAGB and stem biomass. As all the tested models used Ln transformation, a correction factor (CF) was calculated for each equation to minimise the systematic bias during the back transformation to biomass value (Sprugel 1983).

The model having the lowest AIC and RSE and the highest Akaike information criterion weight (AICw) and coefficient of determination (adjusted R²) values was considered as best-fit model (Sileshi 2014, Mahmood et al. 2016b). Kullback-Leibler discrepancy and evidence

Table 1 Species, respective sample number, range of diameter at breast height and their wood density

Species	Family	Sample number	Range of diameter at breast height (cm)	Wood density* (kg m ⁻³)
<i>Albezia procera</i>	Fabaceae	85	6.9–70	730
<i>Albizia richardiana</i>	Fabaceae	352	5.1–80.5	580
<i>Albizia saman</i>	Fabaceae	61	7.8–73.2	590
<i>Aphanamixis polystachya</i>	Meliaceae	48	5.1–43.9	620
<i>Artocarpus heterophyllus</i>	Moraceae	64	5.9–55.4	580
<i>Lannea coromandelica</i>	Anacardiaceae	34	8.3–38.2	495
<i>Mengifera indica</i>	Anacardiaceae	59	7.2–62.7	540
<i>Swietenia macrophylla</i>	Meliaceae	49	4.8–51.6	500
<i>Syzygium cumini</i>	Myrtaceae	65	7.5–53.2	701

*Sattar et al. (1999)

ratio were also calculated to determine the best-fit model between the models having 1st and 2nd highest AICw value (Wagenmakers and Farrell 2004). Test of multicollinearity is important for models containing identical multiple independent variables (Sileshi 2014). Multicollinearity among the independent variables of a model (model contained more than one independent variable) was tested using variance influential factor (VIF) according to Allison (1999). Models having VIF > 5 indicate the existence of multicollinearity among the independent variables (Sileshi 2014). Data was analysed using R (3.2.3) statistical software.

Model evaluation and comparison

The derived best-fit TAGB model was compared and evaluated with frequently used pan-tropical models of Brown (1997), Brown et al. (1989), Nelson et al. (1999), Chave et al. (2005), (2014), Djomo et al. (2010) in terms of model efficiency (ME) and RMSE (Mayer and Butler 1993). Regression between predicted biomass (Yp) (in the X-axis) and observed biomass (Yo) (in the Y-axis) were also derived for the best-fit TAGB model, and the studied pan-tropical models. Significance of slope (b = 1) and intercept (a = 0) were tested in accordance with Piñeiro et al. (2008), which helped to understand graphically the overestimation or underestimation of each predicted biomass value from 1:1 line (Sileshi 2014).

RESULTS

Biomass expansion factor (BEF)

The best-fit BEF model for the trees was $BEF = \exp(3.8839-D)^{0.1072} + \exp(0.8791) * D/H^2 + 1$ with lowest RMSE (0.2580) and second lowest AIC (25.3735) values compared to the other models (Table 2).

Selection of allometric model

Model 6 was derived as the best-fit TAGB allometric model due to its lowest AIC (98.8925) and third lowest RSE (0.2599) value, while model 3 was derived as a close competitor of model 6 with similar value of adjusted R² (0.9455), and second lowest RSE (0.2595) and AIC (98.9687) values. Model 6 showed the highest AICw value (0.3526) compared to model 3 (0.3394). Model 4 of TAGB showed the highest adjusted R² value (0.9456) and first lowest RSE (0.2597), among the eight tested models. However, model 4 showed unaccepted VIF value (VIF > 5) for the three independent variables (D, D², D³) (Table 3). Kullback-Leibler discrepancy and evidence ratio for model 6 and model 3 were 1.03 and 0.51 respectively.

Nevertheless, model 3 of stem biomass appeared as the best-fit allometric model with lowest AIC (76.4168) and RSE (0.2550), and highest adjusted R² (0.9585) values. The AICw value of this model was 1.000, indicating the absence of a close competitor (Table 4).

Table 2 Comparison among the derived models of biomass expansion factor (BEF) for the village forest

BEF equation	a	b	c	Adjusted R ²	AIC	RMSE
BEF = a + b*D	3.5049	-0.2573	-	0.2732	35.7229	0.3388
BEF = a*exp(D*b)	2.2125	-0.0136	-	0.2225	43.1005	0.3504
BEF = a*H^b	5.8501	-0.5375	-	0.5593	19.2532	0.2638
BEF = a*exp(H*b)	2.7127	-0.0445	-	0.4668	27.2545	0.2902
BEF = a*(D*H)^b	6.0245	-0.2408	-	0.4588	27.8840	0.2923
BEF = a - (D*H)^b	3.8316	0.1430	-	0.3820	33.4559	0.3124
BEF = a*(D/H)^b	1.3904	0.1878	-	-0.0231	54.6294	0.4019
BEF = a*exp(D/H)^b	1.3504	0.0778	-	-0.0314	54.9680	0.4036
BEF = exp(a - D)^b + exp(c)*D + 1	12.3520	0.0724	-5.6536	0.3531	43.3777	0.3196
BEF = exp(a - D)^b + exp(c)*D/H^2 + 1	3.8839	0.1072	0.8791	0.5786	25.3735	0.2580

D = diameter at breast height (cm), H = total height (m), AIC = Akaike information criterion, RMSE = root mean square error, a, b and c are model coefficients

Model evaluation and comparison

The model efficiency values for the best-fit model of TAGB was 0.949, which was closest to reference value 1. The RMSE value was also the lowest compared to pan-tropical models. Nevertheless, among the pan-tropical models, Nelson et al. (1999) scored the second position (Table 5). The graphical presentation of 1:1 line indicated that pan-tropical models overestimated TAGB in data set B. Thus, the best-fit TAGB model showed higher accuracy than pan-tropical models (Figure 2).

DISCUSSION

Development of allometric biomass models and selection of best-fit model require extensive field and laboratory work, statistical analysis, critical analysis on model selection criteria and model validation process (Sileshi 2014, Picard et al. 2015, Mahmood et al. 2019a). The selection of appropriate model is a critical task that can considerably reduce the bias in biomass estimation (Nam et al. 2016). Models 6 and 3 are the best-fit models for TAGB and stem biomass (Tables 3 and 4). Models with single independent variable such as D have shown lower efficiency in terms of model selection criterias, but higher efficiency compared to models with multiple independent variables (D, H and W). Inclusion of multiple independent variables in a common biomass model is able to capture more variabilities from diameter, height and species-specific wood density of the sampled trees (Chave et al. 2005, 2014). Both, the best-fit models of TAGB and stem biomass, have included W as an independent variable along with D and H. Thus, W is an important independent variable for multi species common biomass models, to capture the variabilities among the species (Brown et al. 1989, Nelson et al. 1999, Chave et al. 2005, Chave et al. 2014, Njana et al. 2016, Mahmood et al. 2019b). The wood density values that were used for the development of allometric biomass models were not measured for this study. This study used wood density values from the database of Sattar et al. (1999). The database contained heartwood density of different tree species in Bangladesh. The wood density of a species varies with age and position of wood samples, such as base to top of the stem and center to periphery of a

stem disk (Picard et al. 2015). These variations in wood density were not considered during the development of these allometric biomass models, which was one of the limitation of this study. Therefore, the use of wood density values from a database for a particular tree species may yield bias during the estimation of tree or forest biomass (Manuri et al. 2014).

Allometric biomass models can be developed by adopting direct and indirect methods. Direct method involves felling of trees, while indirect method includes volume measurement of stem, use of wood density and BEF (Picard et al. 2015). The allometric models derived from direct method are more accurate compared to the models derived from indirect method (Ketterings et al. 2001, Njana 2017). The accuracy level of allometric models of indirect method varies with nature of independent parameters. Indirect models with species-specific wood density and predicted tree specific BEF have shown higher accuracy in biomass estimation compared to models containing fixed wood density and mean BEF (Njana 2017). Considering the independent parameters (species-specific wood density and predicted tree specific BEF) involved, the current derived allometric models may perform better than other types.

In a comparison, TAGB of sampled trees in data set B were estimated using the best-fit model and frequently used pan-tropical allometric models, which showed wide variation in biomass estimation. The graphical presentation of 1:1 line indicated that pan-tropical models generated a wide range of overestimation compared to the observed biomass (Figure 2). Similarly, wide variation in biomass estimation was observed during comparison of hill and sal forests in Bangladesh, peat swamp forest in Indonesia, Papua tropical forest in Indonesia, evergreen forest in Vietnam, natural forest in Colombia, Kalimantan forest in Indonesia and Sarawak forest in Malaysia (Basuki et al. 2009, Kenzo et al. 2009, Alvarez et al. 2012, Manuri et al. 2014, Nam et al. 2016, Maulana et al. 2016, Mahmood et al. 2019 a, b). This indicated that frequently used pan-tropical biomass models have shown poor prediction capacity. Differences in diameter and height range, range of wood density, tree species and their architecture, forest types and their management practices, site quality and the climatic condition

Table 3 Parameter estimate and comparison among the allometric models of total above ground biomass (TAGB) for the village forest

Model no.	Allometric equation	a	b	c	d	e	Adjusted R ²	RSE	AIC	AICw	CF	VIF
1	Ln (TAGB) = a + b Ln (D)	-0.8544	1.9861				0.9392	0.2746	168.2895	0.0000	1.0384	
2	Ln (TAGB) = a + b Ln (D) + c Ln (H)	-0.8128	2.0313	-0.0738			0.9395	0.2737	165.9522	0.0000	1.0382	a = 2.203, b = 2.203
3	Ln (TAGB) = a + b Ln (D) + c Ln (H) + d Ln (W)	-5.9281	2.0004	-0.0468	0.8069		0.9455	0.2595	98.9687	0.3394	1.0344	a = 2.222, b = 2.230, c = 1.022
4	Ln (TAGB) = a + b Ln (D) + c Ln (D) ² + d Ln (D) ³ + e Ln (W)	-5.0272	0.8074	0.4431	-0.0539	0.8138	0.9456	0.2591	99.1626	0.3080	1.0343	a = 3382.299, b = 14243.235, c = 3865.938, d = 1.011
5	Ln (TAGB) = a + b Ln (D ² * H * W)	-5.5534	0.7220				0.8997	0.3528	494.0709	0.0000	1.0642	
6	Ln (TAGB) = a + b Ln (D) + c Ln (W)	-6.0325	1.9715	0.8193			0.9455	0.2599	98.8925	0.3526	1.0344	a = 1.000, b = 1.010
7	Ln (TAGB) = a + b Ln (D ² *H)) + c Ln (W)	-7.6108	0.7186	1.0495			0.9005	0.3510	489.4362	0.0000	1.0636	a = 1.000, b = 1.009
8	Ln (TAGB) = a + b Ln (D ² *H)	-0.9657	0.7239				0.8903	0.3689	552.2326	0.0000	1.0704	

D = diameter at breast height (cm), H = total height (m), W = wood density (kg m⁻³), a, b, c, d and e are model coefficients, RSE = residual standard error, AIC = Akaike information criterion, AICw = Akaike information criterion weight, CF = correction factor, VIF = variance influential factor

Table 4 Parameter estimate and comparison among the allometric models of stem biomass for the village forest

Model no.	Allometric equation	a	b	c	d	e	Adjusted R ²	RSE	AIC	AICw	CF
1	Ln (Stem) = a + b Ln (D)	-2.1206	2.2380				0.9398	0.3079	317.2584	0.0000	1.0485
2	Ln (Stem) = a + b Ln (D) + c Ln (H)	-2.3915	1.9434	0.4810			0.9532	0.2711	153.9896	0.0000	1.0375
3	Ln (Stem) = a + b Ln (D) + c Ln (H) + d Ln (W)	-7.8134	1.9106	0.5097	0.8553		0.9585	0.2550	76.4168	1.0000	1.0332
4	Ln (Stem) = a + b Ln (D) + c Ln (D) ² + d Ln (D) ³ + e Ln (W)	-4.5988	-0.3186	1.0416	-0.1336	0.6943	0.9460	0.2909	249.2266	0.0000	1.0434
5	Ln (Stem) = a + b Ln (D) ² * H * W	-7.7645	0.8367				0.9521	0.2745	167.8799	0.0000	1.0384
6	Ln (Stem) = a + b Ln (D) + c Ln (W)	-6.6765	2.2252	0.7208			0.9435	0.2979	276.2425	0.0000	1.0454
7	Ln (Stem) = a + b Ln (D) ² * H) + c Ln (W)	-8.5296	0.8355	0.9585			0.9522	0.2742	168.3701	0.0000	1.0384
8	Ln (Stem) = a + b Ln (D) ² * H)	-2.4604	0.8403				0.9454	0.2931	253.4180	0.0000	1.0439

D = diameter at breast height (cm), H = total height (m), W = wood density (kg m⁻³), a, b, c, d and e are model coefficients, RSE = residual standard error, AIC = Akaike information criterion, AICw = Akaike information criterion weight, CF = correction factor

Table 5 Comparing among the best-fit TAGB models of this study and frequently used pan-tropical models

Model no.	Source	Equation	Type	ME	RMSE
6	Present study	Ln (TAGB) = -6.0325+1.9715*Ln (D)+0.8193*Ln (W)	Common	0.949	7521.85
1	Brown, 1997 (Moist)	TAGB = exp(-2.134+2.5430*Ln (D))	Pan-tropical	-2.481	61947.382
3	Nelson et al. (1999)	Ln (TAGB) = -1.8985+2.1569*Ln (D)+0.3888*Ln (H)+0.7218*Ln (W)	Central amazon	0.546	22376.647
4	Chave et al. (2005)	TAGB = W*exp(-1.499+2.148*Ln(D)+0.207*(Ln (D))^2-0.0281*(Ln(D))^3)	Pan-tropical	-3.003	66428.955
5	Brown et al. (1989) (Moist)	TAGB = exp(-2.4090+0.9522*Ln(D) ² *H*W))	Pan-tropical	0.067	32068.848
6	Chave et al. (2005)	TAGB = exp(-2.977+Ln(D) ² *H*W))	Pan-tropical	0.287	28035.494
7	Chave et al. (2014)	TAGB = exp(-2.6986+0.976*Ln(D) ² *H*W))	Pan-tropical	0.208	29547.356
8	Brown et al. (1989) (Moist)	TAGB = exp(-3.1141+0.9719*Ln(D) ² *H))	Pan-tropical	0.000	33205.141
9	Djomo et al. (2010)	Ln (TAGB) = -3.2249+0.9885*Ln(D) ² *H)	Tropical Africa	-0.305	37933.184

D = diameter at breast height (cm), H = total height (m), W = wood density (kg m⁻³), ME = model efficiency, RMSE = root mean square error

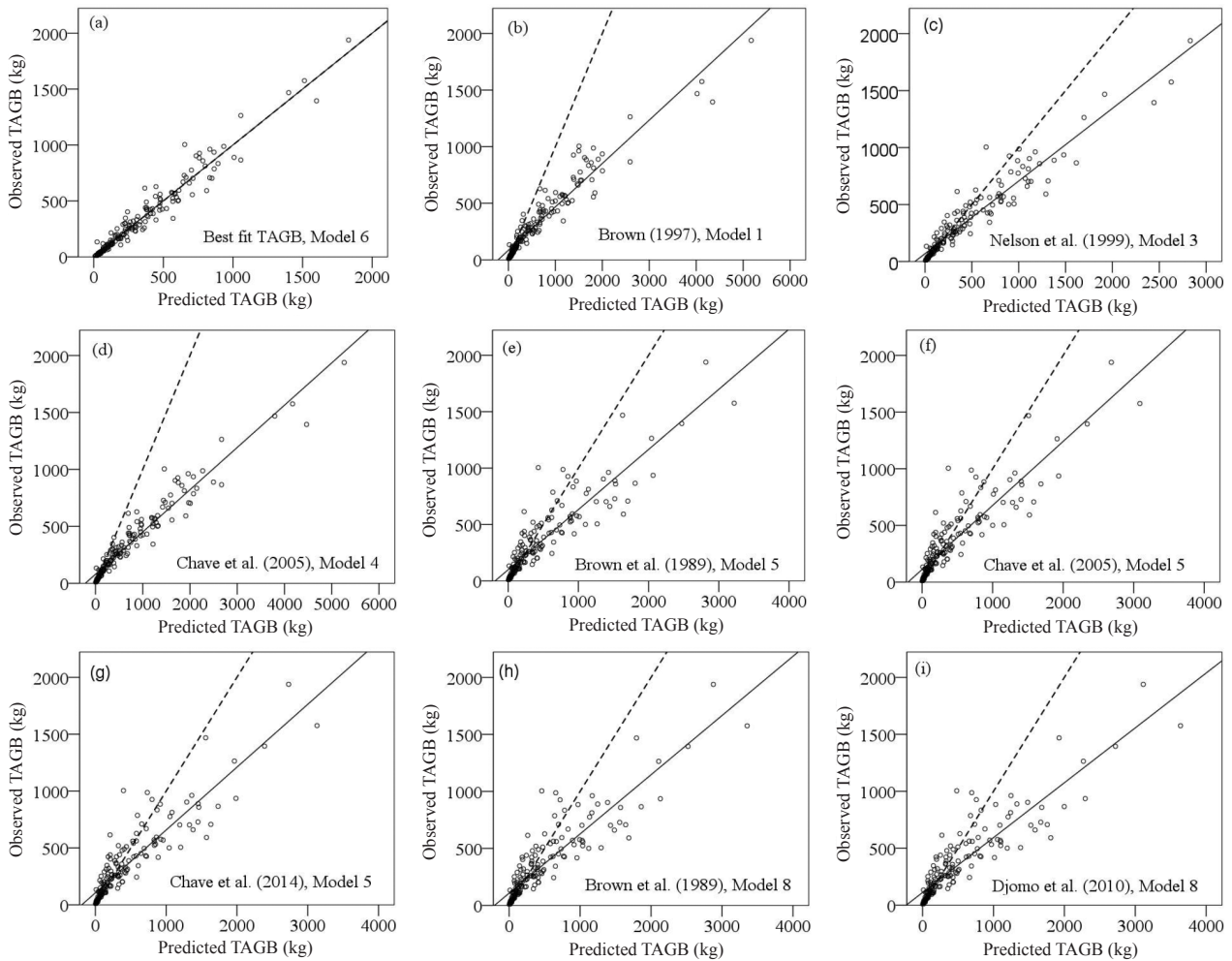


Figure 2 Regression between observed and predicted values of the best-fit common TAGB model of the village zone and frequently used pan-tropical and regional TAGB models; solid line shows regression and broken line shows the significance of slope ($b = 1$) and intercept ($a = 0$)

may influence the efficiency of the compared pan-tropical models (Brown 1989, 1997, Nelson et al. 1999, Chave et al. 2005, Djomo et al. 2010, Chave et al. 2014). Therefore, one should check the variation generated by pan-tropical allometric biomass models before estimating the biomass of a particular forest or species (Alvarez et al. 2012, Nam et al. 2016, Mahmood et al. 2019 a, b). Unfortunately, such comparison for pan-tropical models is rare (Nam et al. 2016). However, the context provided by this study and the results presented herein demonstrated that the currently derived allometric biomass model could accurately estimate the TAGB of the studied species in the village forest of Bangladesh, compared to frequently use pan-tropical models.

CONCLUSION

Pan-tropical models are frequently used to estimate biomass of trees or forests without considering the species, forest types, climatic condition, statistical uncertainty and level of variation or error, which may produce uncertainty in biomass estimation. This study demonstrated that a model with diameter and wood density was more efficient in biomass estimation compared to others. Models with multiple variables are able to capture the variabilities among the species. The derived best-fit TAGB model ($\text{Ln}(\text{TAGB}) = -6.0325 + 1.9715 \cdot \text{Ln}(D) + 0.8193 \cdot \text{Ln}(W)$) accurately estimated the tree biomass of the village forest in Bangladesh, compared to the frequently used pan-tropical allometric

models. Thus, caution need to be taken when using pan-tropical allometric models for the biomass estimation of trees and forest of a particular area.

ACKNOWLEDGEMENT

The authors greatly acknowledge the financial support of Food and Agriculture Organization of the United Nations through GCP/BGD/058/USA (LOA Code: FAOBGDLOA 2017-008) for field and laboratory work. The authors also greatly acknowledge the Bangladesh Forest Research Institute for sharing the volume data of village forest tree species in Bangladesh. Finally, the authors would like to thank the Forestry and Wood Technology Discipline, Khulna University for their logistic supports during laboratory analysis.

REFERENCE

- ALLISON PD. 1999. *Multiple Regression: A Primer*. Pine Forge Press, Thousand Oaks.
- ALVAREZ E, RODRÍGUEZ L, DUQUE A ET AL. 2012. Tree above-ground biomass allometries for carbon stocks estimation in the natural forests of Colombia. *Forest Ecology and Management* 267: 297–308.
- BANGLAPEDIA 2014. *Climate of Bangladesh*. <http://en.banglapedia.org/index.php?title=climate>.
- BASUKI TM, VAN LAAKE PE, SKIDMORE AK & HUSSIN YA. 2009. Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management* 257: 1684–1694.
- BROWN S & LUGO AE. 1992. Above ground biomass estimates for tropical moist forests of the Brazilian Amazon. *Interciencia* 17: 8–18.
- BROWN S, GILLESPIE AJR & LUGO AE. 1989. Biomass estimation method for tropical forests with applications to forest inventory data. *Forest Science* 35: 881–902.
- BROWN S. 1997. *Estimating Biomass and Biomass Change of Tropical Forests: A Primer*. FAO Forestry Paper 134. Food and Agriculture Organization (FAO), Rome.
- CHAVE J, ANDALO C, BROWN S ET AL. 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia* 145: 87–99.
- CHAVE J, RÉJOU-MÉCHAIN M, BÚRQUEZ A ET AL. 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology* 10: 3177–3190.
- DAS DK & ALAM MK. 2001. *Trees of Bangladesh*. Bangladesh Forest Research Institute, Chittagong.
- DJOMO AN, IBRAHIMAB A, SABOROWSKIC J & GRAVENHORST G. 2010. Allometric equations for biomass estimations in Cameroon and pan moist tropical equations including biomass data from Africa. *Forest Ecology and Management* 260: 1873–1885.
- EGGLESTON S, BUENDIA L, MIWA K, NGARA T & TANABE K. 2006. *Guidelines for National Greenhouse Gas Inventories*. Institute for Global Environmental Strategies, Hayama.
- FAO (Food and Agriculture Organization). 2001. *Global Forest Resource Assessment 2000*. FAO Forestry Paper 140. FAO, Rome.
- HASANUZZAMAN M, MAHMOOD H & SAROAR M. 2014. Diversity and preference of agricultural crops in the cropland agroforests of southwestern Bangladesh. *International Journal of Crop Science* 7: 364–372.
- JAMAL MS, HOSSAIN MF, ISLAM MS, HELAL MGJ & JAMIL M. 2016. Quantification of Carbon Stock and Tree Diversity of Homegardens in Rangpur District, Bangladesh. *International Journal of Agriculture and Forestry* 6: 169–180.
- KENZO T, FURUTANI R, HATTORI D, KENDAWANG JJ, TANAKA S, SAKURAI K & NINOMIYA I. 2009. Allometric equations for accurate estimation of above-ground biomass in logged-over tropical rainforests in Sarawak, Malaysia. *Journal of Forest Research* 14: 365–372.
- KETERINGS QM, COE R, NOORDWIJK MV, AMAGAU Y & PALM CA. 2001. Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forest. *Forest Ecology and Management* 146: 199–209.
- KOMIYAMA A, POUNGPARN S & KATO S. 2005. Common allometric equations for estimating the tree weight of mangroves. *Journal of Tropical Ecology* 21: 471–477.
- LATIF MA & ISLAM SMZ. 2000. *Volume Tables for 11 Important Tree Species Grown in the Home Gardens of Bangladesh*. Forest Inventory Division, Bangladesh Forest Research Institute, Chittagong.
- LISBOA SN, GUEDES BS, RIBEIRO N & SITOE A. 2018. Biomass allometric equation and expansion factor for a mountain moist evergreen forest in Mozambique. *Carbon Balance Manage* 13: 23. <https://doi.org/10.1186/s13021-018-0111-7>
- LONGUETAUD F, SANTENOISE P, MOTHE F ET AL. 2013. Modeling volume expansion factors for temperate tree species in France. *Forest Ecology and Management* 292: 111–121.
- MAHMOOD H, SABERI O, JAPAR SIDIK B & MISRI K. 2008. Net primary productivity of *Bruguiera parviflora* (Wight & Arn.) dominated mangrove forest at Kuala Selangor, Malaysia. *Forest Ecology and Management* 255: 179–182.
- MAHMOOD H, SAHA C, ABDULLAH SMR, SAHA S & SIDDIQUE MRH. 2016b. Allometric biomass, nutrient and carbon stock models for *Kandelia candel* of the Sundarbans, Bangladesh. *Trees* 30: 709–717.
- MAHMOOD H, SIDDIQUE M, COSTELLO L ET AL. 2019b. Allometric models for estimating biomass, carbon and nutrient stock in the Sal Zone of Bangladesh. *iForest* 12: 69–75.
- MAHMOOD H, SIDDIQUE MRH & AKHTER M. 2016a. A critical review and database of biomass and volume allometric equation for trees and shrubs of Bangladesh. IOP Conference Series. *Earth and Environmental Science* 39: 012057.
- MAHMOOD H, SIDDIQUE MRH, ISLAM SMZ, ABDULLAH SMR, MATIEU H, IQBAL MZ & AKHTER M. 2019a. Applicability of semi-destructive method to derive allometric model for estimating aboveground biomass and carbon stock in the Hill zone of Bangladesh. *Journal of Forestry Research*. <https://doi.org/10.1007/s11676-019-00881-5>

- MAHMOOD H. 2014. Carbon pools and fluxes in *Bruguiera parviflora* dominated naturally growing mangrove forest of Peninsular Malaysia, *Wetland Ecology and Management* 22: 15–23.
- MANURI S, BRACK C, NUGROHO NP ET AL. 2014. Tree biomass equations for tropical peat swamp forest ecosystems in Indonesia. *Forest Ecology and Management* 334: 241–253.
- MAULANA SI, WIBISONO Y & UTOMO S. 2016. Development of local allometric equation to estimate total aboveground biomass in Papua tropical forest. *Indonesian Journal of Forest Research* 3: 107–118.
- MAYER D & BUTLER D. 1993. Statistical validation. *Ecological Modeling* 68: 21–32.
- MIAH MD, UDDIN MF, BHUIYAN MK, KOIKE M & SHIN MY. 2009. Carbon sequestration by the indigenous tree species in the reforestation program in Bangladesh-*Aphanamixis polystachya* Wall. and Parker. *Forest Science and Technology* 5: 62–65.
- MILLATE-E-MUSTAFA MD, HALL JB & TEKLEHAIMANOT Z. 1996. Structure and floristics of Bangladesh home gardens. *Agroforest System* 33: 263–280.
- NAM VT, VAN KUIJK M & ANTEN NPR. 2016. Allometric Equations for Aboveground and Belowground Biomass Estimations in an Evergreen Forest in Vietnam. *PLoS ONE* 11 . e0156827. Doi:10.1371/journal.pone.0156827
- NELSON BW, MESQUITA R, PEREIRA JLG, SOUZA SGAD, BATISTA GT & COUTO LB. 1999. Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. *Forest Ecology and Management* 117: 149–167.
- NJANA MA, MEILBY H, EID T, ZAHABU E & MALIMBW RE. 2016. Importance of tree basic density in biomass estimation and associated uncertainties: a case of three mangrove species in Tanzania. *Annals of Forest Science* 73: 1073–1087.
- NJANA MA. 2017. Indirect methods of tree biomass estimation and their uncertainties, *Southern Forests: a Journal of Forest Science* 79: 41–49.
- PALADINGIĆ E, VULETIĆ D, MARTINIĆ I, MARJANOVIĆ H, INDIR K, BENKO M & NOVOTNY V. 2009. Forest biomass and sequestered carbon estimation according to main tree components on the forest stand scale. *Periodicum Biologorum* 4: 459–466.
- PAUL KI, ROXBURGH SH, RITSON P ET AL. 2013. Testing allometric equations for prediction of above-ground biomass of mallee eucalypts in southern Australia. *Forest Ecology and Management* 310: 1005–1015.
- PICARD N, RUTISHAUSER E, PLOTON P, NGOMANDA A & HENRY M. 2015. Should tree biomass allometry be restricted to power models? *Forest Ecology and Management* 353: 156–163.
- PICARD N, SAINT-ANDRÉ L & HENRY M. 2012. *Manual for Building Tree Volume and Biomass Allometric Equations: From Field Measurement to Prediction*. Food and Agricultural Organization of the United Nations, Rome, and Centre de Coopération Internationale en Recherche Agronomique pour le Développement, Montpellier.
- PIÑEIRO G, PERELMAN S, GUERSCHMAN JP & PARUELO JM. 2008. How to evaluate models: observed vs predicted or predicted vs observed. *Ecological Modeling* 216: 316–322.
- POORTER L, BONGERS F, STERCK FJ & WO'LL H. 2003. Architecture of 53 rain forest tree species differing in adult stature and shade tolerance. *Ecology* 84: 602–608.
- RAHMAN MM, KABIR ME, AKON ASMJU & ANDO K. 2015. High carbon stocks in roadside plantations under participatory management in Bangladesh. *Global Ecology and Conservation* 3: 412–423.
- SANQUETTA, CR, CORTE AP & DA SILVA F. 2011. Biomass expansion factor and root-to shoot ratio for Pinus in Brazil. *Carbon Balance Management* 6: 1–8.
- SATTAR MA, BHATTACHARJEE DK & KABIR MF. 1999. *Physical and Mechanical Properties and Uses of Timbers of Bangladesh*. Bangladesh Forest Research Institute, Chittagong
- SILESHI GW. 2014. A critical review of forest biomass estimation models, common mistakes and corrective measures. *Forest Ecology and Management* 329: 237–254.
- SOARES P & TOME M. 2012. Biomass expansion factors for *Eucalyptus globulus* stands in Portugal. *Forest System* 21: 141–152.
- SPRUGEL DG. 1983. Correcting for bias in log-transformed allometric equations. *Ecology* 64 : 209–210.
- TAEROE A, NORD-LARSEN T, STUPAK I & RAULUND-RASMUSSEN K. 2015. Allometric biomass, biomass expansion factor and wood density models for OP42 hybrid Poplar in Southern Scandinavia. *BioEnergy Research* 8: 1332–1343.
- ULLAH MR & AL-AMIN M. 2012. Above- and below-ground carbon stock estimation in a natural forest of Bangladesh. *Journal of Forest Science* 58: 372–379.
- WAGENMAKERS EJ & FARRELL S. 2004. AIC model selection using Akaike weights. *Psychonomic Bulletin and Review* 11: 192–196.