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Development and Evaluation of Species-Specific Biomass Models for Most Common Timber and Fuelwood Species of Bangladesh

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Abstract

Allometric biomass models are efficient tools to estimate biomass of trees and forest stands in a non-destructive way. Development of species-specific allometric biomass models requires extensive fieldwork and time. Our study aimed to generate species-specific allometric biomass models for the most common fuelwood and timber species of Bangladesh. We also wanted to evaluate the performances of our models relative to the performances of regional and commonly used pan-tropical biomass models. We used semi-destructive method that incorporates tree-level volume, species-specific biomass expansion factor (BEF), and wood density. We considered four base models, 1) Ln (biomass) = a + bLn (D); 2) Ln (biomass) = a + bLn (H); 3) Ln (Biomass) = a + bLn (D^2H); 4) Ln (Biomass) = a + bLn (D) + cLn (H) to develop species-specific best-fitted models for Total Above-Ground Biomass (TAGB) and stem biomass. The best-fitted model for each species was selected by the lowest value of Akaike Information Criterion (AIC), Residual Standard Error (RSE) and Root Mean Square Error (RMSE). The derived best-fitted models were then evaluated with respect to regional and pan-tropical models using a separate set of observed data. This evaluation was conducted by computing ME (Model Efficiency) and MPE (Model Prediction Error). The best-fitted allometric biomass models have shown higher model efficiency (0.85 to 0.99 at scale 1) and the lowest model prediction error (−8.94% to 5.27%) compared to the regional and pan-tropical models. All the examined regional and pan-tropical biomass models showed different magnitude of ME and MPE.

Some models showed higher level (>0.90 at scale 1) of ME compared to the best-fitted specific species biomass model.

Keywords

Allometry, Bangladesh, Biomass, Fuelwood, Timber, Pan-Tropical Model, Regional Common Model

1. Introduction

Bangladesh has 17.48% of forestland that ecologically can be classified into three types as tropical evergreen and semi-evergreen forest, tropical moist deciduous forest and mangrove forest (FD, 2017). This country has 163.05 million of population with a density of 1116 person/km^2 that ranks 10th position in the world (World Population Review, 2019). This large population imposes immense pressure on natural resources of this country (Reza & Sharmin, 2016) that also influences the forestry sector through deforestation and degradation of forestlands (FRA, 2000; World Bank, 2016). Recently, Bangladesh has initiated REDD+ activities to reduce emissions of greenhouse gases from deforestation and degradation, conservation and enhancement of forest-carbon stocks, and sustainable management of forests (FD, 2019). Therefore, success of REDD+ activities depends on authenticated data and information on the existing forest areas and their conditions.

Forest inventory is an integral part of forest management as it provides data and information on trees and forest resources. A total of 19 forest inventories were conducted in Bangladesh by Bangladesh Forest Department since 1960. Overtime, the objectives of forest inventories have been shifted from a focus on volume for timber resources to biomass for carbon-related values to meet the demand of 21st century (FD, 2017). Forest can act as a sink and source of carbon (Canadian Forest Service, 2007). Biomass estimation is an important tool for estimating stock and sequestration of carbon in a forested ecosystem (Golley et al., 1975; Vashum & Jayakumar, 2012; Mahmood, 2014). Biomass of trees and forest can be estimated by following destructive and non-destructive methods (Somogyi et al., 2007; Picard et al., 2012; Mahmood et al., 2015; Wakawa, 2016; Mahmood et al., 2017). Allometric biomass models are frequently used to estimate tree and forest biomass (Somogyi et al., 2007). Destructive, semi-destructive and non-destructive methods are followed to derive species-specific, regional and pan-tropical allometric biomass models (Ketterings et al., 2001; Chave et al., 2005, 2014; Basuki et al., 2009). Destructive method of biomass model development is more accurate compared to others, but this method is usually discouraged from violating regional and/or national forest management policies (Ketterings et al., 2001).

The multi-species regional and pan-tropical biomass models are commonly used for large-scale biomass estimation (Clark & Kellner, 2012; Mahmood et al., 2019a, 2019b, 2019c). The first nationwide forest inventory in Bangladesh was conducted in 2007 where pan-tropical biomass model (Above-ground biomass (tons) = $V* W*$ BEF, where V = volume over bark tons ha^{-1}, W = wood density tons m^{-3} and BEF= biomass expansion factor) of Brown & Lugo (1992) was used to estimate the biomass stock in forest areas. This estimation included a common wood density value (0.57 t·m^{-3}) and a fixed biomass expansion factor (6) (FD, 2007) which may result in uncertainty in biomass estimation by considering a lower wood density and a higher fixed value of biomass expansion factor (Penman et al., 2003). During the year 2009, pan-tropical model of Chave et al. (2005) was also used to estimate the biomass and carbon stock of the Sundarbans of Bangladesh (Rahman et al., 2015). The used pan-tropical model is capable to generalize poorly with its polynomial function that results in implausible relationship among biomass and diameter of trees (Sileshi, 2014). In other ways, pan-tropical biomass model of Brown et al. (1989) and Chave et al. (2005) were commonly used to estimate the biomass and carbon stock in plantation and natural forests of Bangladesh like Miah et al. (2009), Ullah & Al-Amin (2012), Rahman et al. (2015). Numerous studies demonstrated that pan-tropical models generate higher bias in biomass estimation compared to locally developed models (Vieira et al., 2008; Basuki et al., 2009; Kenzo et al., 2009; Ngomanda et al., 2014; Maulana et al., 2016). Therefore, it is recommended to check the bias/deviation in biomass estimation using the multi-species regional and pan-tropical models for a particular species and forests (Alvarez et al., 2012). Simultaneously, species-specific allometric biomass model may significantly reduce bias in biomass estimation compared to the multi-species regional and commonly used pan-tropical models because they may not able to capture the variability of tree properties (height and diameter at breast height relationship, wood density) caused by ecological and management intervention (Nam et al., 2016; Maulana et al., 2016; Mahmood et al., 2019c). Therefore, this study aimed i) to generate species-specific allometric biomass models for the most common fuelwood and timber species of Bangladesh and ii) to evaluate the performances of the derived best-fitted species-specific models in relation to the performances of multi-species regional and commonly used pan-tropical biomass models.

2. Materials and Methods

2.1. Description of the Study Area

Sampled trees of this study were collected from the natural patches and plantations of tropical wet evergreen and semi-evergreen forest, tropical moist deciduous forest of Bangladesh during 2018. Bangladesh lies between 20˚34' and 26˚38' north latitude and 88˚01' and 92˚41' east longitude (**Figure 1**). The rainfall ranges from 1500 mm in the northwest to 5000 mm in the northeast. Mean monthly maximum temperature is 24˚C to 37˚C, while mean monthly relative humidity found to vary from 63% to 83%. Soil texture is silty loam to clay loam and pH range is 5.5 to 8.3 (Banglapedia, 2014). *Albizia procera* (Roxb.) Benth.,

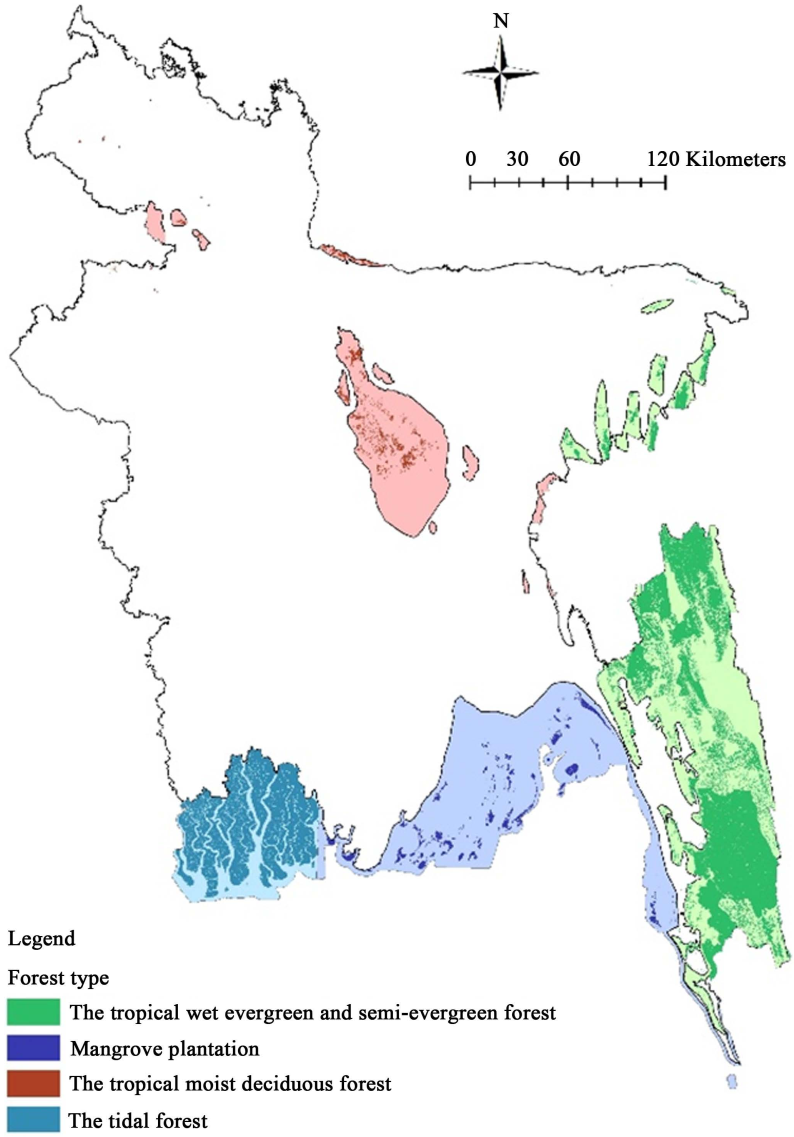

Figure 1. Location of major forest types of Bangladesh.

Albizia richardiana (Voigt) King & Prain, *Dipterocarpus turbinatus* C. F. Gaertn., *Gmelina arborea* Roxb., *Lagerstroemia speciosa* (L.) Pers., *Samanea saman* F. Muell., *Swietenia macrophylla* King, *Syzygium grande* (Wight) Walp. *Tectona grandis* L. f. is the most common timber species found in both natural patches and plantations. While, *Acacia auriculiformis* A. Cunn. ex Benth., *Acacia mangium* Willd., *Dalbergia sissoo* Roxb., *Eucalyptus camaldulensis* Dehnh., *Senna siamea* (Lam.) Irwin et Barneby., are the commonest fuelwood species of Bangladesh that mostly restricted in plantation (Das & Alam, 2001).

2.2. Biomass Expansion Factor (BEF)

2.2.1. Sampling of Trees for Biomass Expansion Factor (BEF)

Twenty individuals of each studied species, which yielded 280 sample trees, were felled from the natural patches and plantations of the study areas. The species were identified using taxonomic key. The sample trees were selected based on subjective judgement to avoid specimens with broken top, hollow trunk, damage caused by natural calamities or animals, and evidence of suppression or disease.

2.2.2. Field Measurement and Laboratory Analysis

Total height and DBH of the sampled tree were measured and felled at ground level. The felled trees were separated into leaves, small branches (diameter < 7 cm), bigger branches (diameter > 7 cm) and stem. Species wise fresh weight of these components of individual sampled tree were measured and recorded in the field (Picard et al., 2012; Mahmood et al., 2019a, 2019b, 2019c). Ten sub samples (0.25 kg) of leaf, smaller branch, and ten disk of disk of bigger branches and stem) of individual species were taken randomly from the felled trees. These sub-samples were oven-dried at 105˚C until a constant weight to estimate the fresh to oven-dry weight conversion factor. The respective conversion factors were used to estimate the oven-dry weight of individual sampled trees (Mahmood et al., 2019a, 2019b, 2019c). Finally, biomass expansion factor (BEF) of individual sampled trees was calculated from the ratio of Total Above-ground Biomass (TAGB) and oven-dry stem biomass, and species-specific average BEF was derived for further use (Taeroe et al., 2015).

$$\text{BEF} = \frac{\text{Total aboveground biomass}}{\text{Oven-dry stem biomass}}.$$

2.3. Allometric Model of Stem and Total Above-Ground (TAGB) Biomass

2.3.1. Data Collection and Compilation

This study used stem volume data of 2490 individuals of 14 most common timber and fuelwood species of Bangladesh that were collected from the natural patches and plantations of tropical wet evergreen and semi-evergreen forest and tropical moist deciduous forest. The mean value with ranges of DBH, H and W of the sampled tree species are presented in **Table 1**. Bangladesh Forest Research Institute collected the stem volume data from the natural patches and plantations of tropical evergreen and semi-evergreen forest, tropical moist deciduous forest of Bangladesh. Stem biomass (kg) of individual sampled tree was estimated from their stem volume (m^3) and wood density (W) ($kg \cdot m^{-3}$) value of the respective tree species as derived by Sattar et al. (1999). TAGB of individual trees was estimated from the stem biomass and species-specific mean BEF.

2.3.2. Allometric Model Development and Evaluation

The independent variables (D and H) and dependent variables (Stem biomass and TAGB) were transformed to Ln (natural logarithm) to improve the linearity and homoscedasticity. Tree volume data was collected in two different occasions. A total of 2490 sample trees (data set A) were selected to derive species-specific allometric biomass model. While, data set B contained 614 individual which was used to validate the derived best-fitted model and comparison with regional and

Table 1. List of studied species and their wood density, range of DBH and Height, sample number in data set A and B and mean biomass expansion factor.

Species	Wood density ($kg \cdot m^{-3}$)	Range of DBH (cm)	Range of Height (m)	Data set A	Data set B	Mean BEF ± SE
Acacia auriculiformis	700	3.9 - 49.4	5.8 - 25.0	567	61	1.39 ± 0.04
Acacia mangium	530	5.0 - 41.8	5.5 - 28.5	260	54	1.41 ± 0.01
Albizia procera	730	6.9 - 70.0	4.5 - 22.0	57	28	1.51 ± 0.12
Albizia richardiana	580	5.1 - 80.5	4.0 - 32.5	271	81	1.50 ± 0.08
Dalbergia sissoo	740	6.8 - 39.3	5.5 - 19.5	56	22	1.31 ± 0.05
Dipterocarpus turbinatus	619	5.5 - 51.0	5.0 - 26.0	170	44	1.47 ± 0.11
Eucalyptus camaldulensis	721	4.5 - 51.2	8.0 - 30.5	264	60	1.35 ± 0.03
Gmelina arborea	540	8.5 - 50.0	6.5 - 22.0	106	31	1.28 ± 0.03
Lagerstroemia speciosa	595	9.5 - 56.3	6.5 - 27.0	257	54	1.49 ± 0.07
Samanea saman	590	5.2 - 39.1	5.9 - 19.7	57	28	1.51 ± 0.14
Senna siamea	660	7.8 - 73.2	6.0 - 25.0	148	51	1.63 ± 0.13
Swietenia macrophylla	537	9.9 - 90.5	6.5 - 32.0	149	58	1.29 ± 0.03
Syzygium grande	673	5.0 - 38.0	5.0 - 27.0	84	30	1.63 ± 0.14
Tectona grandis	720	7.0 - 51.0	9.5 - 26.0	44	12	1.41 ± 0.11

Note: BEF = Biomass Expansion Factor, SE = Standard error of mean.

pan-tropical biomass models. We considered four Ln base models, 1) Ln (biomass) = a + bLn (D); 2) Ln (biomass) = a + bLn (H); 3) Ln (Biomass) = a + bLn (D^2H); 4) Ln (Biomass) = a + bLn (D) + cLn (H) to develop species-specific allometric biomass models for TAGB and stem biomass according to (Picard et al., 2012). The best-fitted models were selected based on the lowest Akaike Information Criterion (AIC), Residual Standard Error (RSE) and Root Mean Square Error (RMSE); and highest coefficient of determination (Adjusted R^2) values (Sileshi, 2014; Mahmood et al., 2019a, 2019b, 2019c). Data were analyzed using R (3.2.3) statistical software. A correction factor (CF) was calculated for each equation to minimize the systematic bias during the back transformation to biomass value (Sprugel, 1983). The derived best-fitted TAGB models were compared and evaluated with the multi-species regional and common pan-tropical models (**Table 2**) in terms of Model Efficiency (ME) and Model Prediction Error (MEP) (Mayer & Butler, 1993).

3. Results

3.1. Selection of Allometric Model

Model 4 (Ln (biomass) = a + bLn (D) + Ln (H)) has appeared as best-fit TAGB and stem biomass allometric model for *A. auriculiformis*, *A. procera*, *A. richardiana*, *E. camaldulensis*, *G. arborea*, *L. speciosa*, *S. saman*, *S. siamea* and *S. grande* due to its lowest AIC, RSE and RMSE values. While, Model 3

Table 2. Multi-species regional and commonly used pan-tropical allometric biomass models.

Source	Allometric biomass model	Type
Mahmood et al., 2019a (Tropical moist deciduous forest)	Ln (TAGB) = −2.460 + 2.171 Ln (D) + 0.367 Ln (H) + 0.161 Ln (W)	Regional multi-species, Bangladesh
Mahmood et al., 2019b (Tropical evergreen and semi-evergreen forest)	Ln (TAGB) = −6.6937 + 0.809 Ln (D^2HW)	Regional multi-species, Bangladesh
Brown et al. (1989) (Moist)	TAGB = exp (−2.4090 + 0.9522 Ln (D^2HW))	Pan-tropical
Chave et al. (2005)	TAGB = exp (−2.977 + Ln (D^2HW))	Pan-tropical
Chave et al. (2014)	TAGB = exp (−2.6986 + 0.976 Ln (D^2HW))	Pan-tropical

Note: TAGB = Total aboveground biomass, D = Diameter at Breast Height, H = Total Height, W = Wood density.

(Ln (biomass) = a + bLn (D^2H)) found to be best-fit TAGB and stem allometric biomass model for *A. mangium*, *D. sissoo*, *D. turbinatus*, *S. macrophylla* and *T. grandis* considering the model selection criteria (**Table 3** and **Table 4**).

3.2. Model Evaluation and Comparison

The model efficiency and model prediction error values of the best-fitted TAGB models of the studies species found to vary from 0.85 to 0.99 (at scale 1) and −8.94% to 5.27% respectively. Lower model efficiency and higher prediction error were observed for *S. saman*, *S. macrophylla* and *A procera*, while the highest model efficiency and lower prediction error were observed for *A. mangium*, *E. camaldulensis* and *T. grandis* (**Table 5**).

The best-fitted TAGB model of all the studied species except *A. procera*, *L. speciosa* and *S. saman* showed higher performance in biomass estimation compared to the regional and commonly used pan-tropical allometric models in relation to model efficiency and model prediction error values. TAGB model of Chave et al. (2014) and Chave et al. (2005) have appeared as more efficient in biomass estimation of *A. procera* and *L. speciosa* respectively. While, TAGB models of Mahmood et al. (2019a) and Chave et al. (2014) can efficiently estimate the biomass of *S. saman* compared to the derived model (**Table 5**).

4. Discussion

Alometric biomass models are important tools to estimate biomass of standing trees and stands (Golley et al., 1975; Basuki et al., 2009) and the accuracy in the estimation depends on model efficiency (Sileshi, 2014). Method of model development, involvement of independent variables and model selection criteria influence the efficiency of allometric biomass model (Sileshi, 2014; Picard et al., 2012). Generally, wood density (W), Diameter at Breast Height (DBH) and total height (H) are considered as independent variables of allometric biomass models (Picard et al., 2012). Wood density of a species varies among the ecoregion (Zanne et al., 2009). This study considered DBH and H as independent variables. But, W was not included because the sample trees were collected from the same ecoregion that likely to have similar wood density for a particular species

Table 3. Species-specific best-fitted allometric biomass model for Total Above-Ground Biomass (TAGB).

Species name	Best-fitted allometric biomass model	Adjusted R^2	AIC	RSE	RMSE	CF
Acacia auriculiformis	Ln (TAGB) = −2.459 + 1.869 Ln (D) + 0.800 Ln (H)	0.986	−760.515	0.123	0.123	1.007
Acacia mangium	Ln (TAGB) = −3.005 + 0.923 Ln (D^2H)	0.984	−276.327	0.141	0.141	1.010
Albizia procera	Ln (TAGB) = −1.984 + 1.911 Ln (D) + 0.572 Ln (H)	0.969	−13.870	0.205	0.205	1.021
Albizia richardiana	Ln (TAGB) = −2.111 + 1.832 Ln (D) + 0.648 Ln (H)	0.972	−62.744	0.214	0.214	1.023
Dalbergia sissoo	Ln (TAGB) = −2.608 + 0.905 Ln (D^2H)	0.985	−53.709	0.145	0.145	1.010
Dipterocarpus turbinatus	Ln (TAGB) = −2.525 + 0.897 Ln (D^2H)	0.974	−67.920	0.196	0.196	1.019
Eucalyptus camaldulensis	Ln (TAGB) = −2.663 + 1.915 Ln (D) + 0.832 Ln (H)	0.989	−349.155	0.124	0.124	1.008
Gmelina arborea	Ln (TAGB) = −2.421 + 1.585 Ln (D) + 1.011 Ln (H)	0.976	−102.663	0.146	0.146	1.011
Lagerstroemia speciosa	Ln (TAGB) = −2.909 + 1.976 Ln (D) + 0.829 Ln (H)	0.968	−199.884	0.162	0.150	1.013
Samanea saman	Ln (TAGB) = −2.461 + 1.933 Ln (D) + 0.660 Ln (H)	0.984	−24.594	0.167	0.167	1.014
Senna siamea	Ln (TAGB) = −2.597 + 1.835 Ln (D) + 0.951 Ln (H)	0.992	−289.357	0.090	0.090	1.004
Swietenia macrophylla	Ln (TAGB) = −2.302 + 0.894 Ln (D^2H)	0.974	−89.208	0.177	0.177	1.016
Syzygium grande	Ln (TAGB) = −2.713 + 1.529 Ln (D) + 1.324 Ln (H)	0.968	−7.211	0.225	0.225	1.026
Tectona grandis	Ln (TAGB) = −2.180 + 0.875 Ln (D^2H)	0.973	−25.420	0.173	0.173	1.015

Note: AIC = Akaike Information Criterion, RSE = Residual Standard Error, RMSE = Root Mean Square Error, CF = Correction Factor.

Table 4. Species-specific best-fitted allometric biomass model for Stem.

Species name	formula	Adjusted R^2	AIC	RSE	RMSE	CF
Acacia auriculiformis	Ln (Stem) = −2.787 + 1.869 Ln (D) + 0.800 Ln (H)	0.985	−760.631	0.123	0.123	1.007
Acacia mangium	Ln (Stem) = −3.327 + 0.923 Ln (D^2H)	0.984	−276.356	0.141	0.141	1.010
Albizia procera	Ln (Stem) = −2.396 + 1.911 Ln (D) + 0.572 Ln (H)	0.969	−13.870	0.205	0.205	1.021
Albizia richardiana	Ln (Stem) = −2.532 + 1.832 Ln (D) + 0.648 Ln (H)	0.972	−62.742	0.214	0.214	1.023
Dalbergia sissoo	Ln (Stem) = −2.878 + 0.904 Ln (D^2H)	0.985	−53.709	0.145	0.145	1.011
Dipterocarpus turbinatus	Ln (Stem) = −2.911 + 0.897 Ln (D^2H)	0.974	−67.922	0.196	0.196	1.019
Eucalyptus camaldulensis	Ln (Stem) = −2.963 + 1.915 Ln (D) + 0.832 Ln (H)	0.989	−349.194	0.124	0.124	1.008
Gmelina arborea	Ln (Stem) = −2.668 + 1.585 Ln (D) + 1.011 Ln (H)	0.976	−102.663	0.146	0.146	1.011
Lagerstroemia speciosa	Ln (Stem) = −3.307 + 1.976 Ln (D) + 0.829 Ln (H)	0.968	−199.882	0.162	0.162	1.013
Samanea saman	Ln (Stem) = −2.873 + 1.933 Ln (D) + 0.660 Ln (H)	0.984	−24.594	0.167	0.167	1.014
Senna siamea	Ln (Stem) = −3.057 + 1.835 Ln (D) – 0.951 Ln (H)	0.992	−289.374	0.090	0.008	1.004
Swietenia macrophylla	Ln (Stem) = −2.556 + 0.894 Ln (D^2H)	0.974	−89.208	0.177	0.177	1.016
Syzygium grande	Ln (Stem) = −3.202 + 1.529 Ln (D) + 1.324 Ln (H)	0.968	−7.211	0.225	0.225	1.026
Tectona grandis	Ln (Stem) = −2.524 + 0.875 Ln (D^2H)	0.973	−25.420	0.173	0.173	1.015

Note: AIC = Akaike Information Criterion, RSE = Residual Standard Error, RMSE = Root Mean Square Error, CF = Correction Factor.

Table 5. Comparison of species-specific best-fitted TAGB model with regional and commonly used pan-tropical allometric biomass models.

Species	Best-fitted		Mahmood et al. (2019a)		Mahmood et al. (2019b)		Brown et al. (1989)		Chave et al. (2005)		Chave et al. (2014)	
	ME	MPE (%)	ME	MPE (%)	ME	MPE (%)	ME	MPE (%)	ME	MPE (%)	ME	MPE (%)
Acacia auriculiformis	0.95	2.62	0.89	−31.15	0.83	55.66	0.61	28.01	0.75	6.21	0.70	15.78
Acacia mangium	0.99	0.12	0.93	−15.56	0.86	63.51	0.84	25.46	0.94	1.59	0.91	12.11
Albizia procera	0.94	−8.94	0.82	−27.28	0.94	23.57	0.88	6.34	0.94	−10.86	0.93	−3.30
Albizia richardiana	0.94	3.18	0.91	−9.83	0.74	44.05	0.51	30.97	0.71	11.83	0.64	20.20
Dalbergia sissoo	0.96	−3.29	0.83	−17.59	0.91	53.72	0.83	31.73	0.94	10.36	0.90	19.75
Dipterocarpus turbinatus	0.98	1.44	0.87	−23.32	0.90	39.40	0.84	13.83	0.93	−5.96	0.90	2.74
Eucalyptus camaldulensis	0.99	−1.79	0.72	−38.68	0.93	49.10	0.84	27.21	0.90	6.60	0.89	15.64
Gmelina arborea	0.96	2.00	0.90	0.28	0.10	52.10	0.15	30.07	0.63	8.67	0.45	18.10
Lagerstroemia speciosa	0.96	5.27	0.81	−15.99	0.94	28.71	0.87	16.65	0.94	−0.72	0.92	6.89
Samanea saman	0.85	−6.55	0.86	−4.41	0.84	18.08	0.78	8.61	0.82	−7.01	0.81	−0.19
Senna siamea	0.97	0.89	0.70	−41.58	0.94	28.43	0.96	−1.44	0.95	−20.39	0.97	−12.01
Swietenia macrophylla	0.93	4.66	0.84	−35.00	0.90	−10.02	0.91	−6.43	0.89	−16.22	0.91	−12.09
Syzygium grande	0.94	0.66	0.72	−37.67	0.92	28.26	0.90	1.28	0.95	−17.29	0.94	−9.11
Tectona grandis	0.99	−1.33	0.65	−36.10	0.97	7.45	0.84	7.88	0.94	2.20	0.91	4.65

Note: ME = Model efficiency, MPE = Model prediction error.

(Kusmana et al., 2018). Moreover, W is not recommended as independent variable for species-specific allometric models development due to its lower performance and robustness in use (Njana et al., 2016). Inclusion of more than one independent variable likely to increase the efficiency of allometric models to capture more variabilities (Ketterings et al., 2001; Chave et al., 2005). Our study showed that models with H and DBH have higher efficiency for all the studied species and similar findings were also reported by Rutishauser et al. (2013); Kusmana et al. (2018) and Khushi et al. (2019). Allometric models with single independent variable (DBH) are robust in the field measurement and biomass estimation (Ketterings et al., 2001; Chave et al., 2014; Istrefi et al., 2019). But, DBH as single independent variable has shown lower efficiency in model selection parameters of this study.

Model validation is an important stage to precribe best-fitted allometric biomass model for a group of species or single species (Sileshi, 2014). Different predictive performance (goodness-of-fit) statistics like ME, MPE, Roor Mean Squared Relative Prediction Error, graphical presentation of 1:1 line etc. are followed to evaluate performance of best-fitted models (Makungwa et al., 2013; Sileshi, 2014; Huy et al., 2016; Mahmood et al., 2019a, 2019b, 2019c). Best-fitted model of the studied species (except *A. procera, S. saman* and *L. speciosa*) showed higher predictive performance in biomass estimation compared to the regional and pan-tropical models. The variation in estimated biomass may be due to the differences in tree species, climatic conditions, site conditions, forest types with its composition and management practices which ultimately influence the architecture of tree and biomass partitioning (Poorter et al., 2006; Iida et al., 2011; Mugasha et al., 2016; Nam et al., 2016). Development of species-specific allometric models is quite laborious and time-consuming efforts (Picard et al., 2012). Therefore, regional and pan-tropical allometric biomass models are frequently used to estimate biomass of tree species those do not have species-specific model (Chave et al., 2014). Such application of regional or pantropical models may produce higher variation in biomass estimation compared to species specific allometric biomass models (Ketterings et al., 2001; Ngomanda et al., 2014). However, the species-specific best-fitted allometric models of *A. procera*, *L. speciosa* and *S. saman* in this study showed lower efficiency compared to some regional and pan-tropical models. Therefore, the regional and pan-tropical biomass models can be used to estimate the species-specific biomass prior checking the range of variation generated by using those (Alvarez et al., 2012).

5. Conclusion

Allometric biomass models with DBH and H showed higher efficiency in model selection parameters for all the studied species. Most of the best-fitted biomass models showed higher model efficiency and lower model prediction error compared to the regional and pan-tropical models. Our study suggests using species-specific allometric models for biomass estimation for higher accuracy. In absence of species-specific models, ME and MPE need to be checked for the regional- and pan-tropical models to reduce uncertainties in large scale biomass estimation.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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