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Aboveground biomass equations for evergreen broadleaf forests in South Central Coastal ecoregion of Viet Nam: Selection of eco-regional or pantropical models

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ABSTRACT

As part of Viet Nam's effort to participate in REDD+ (reducing emissions from deforestation and forest degradation), selected biomass equations were evaluated for their predictive abilities using data collected from destructively sampled 110 trees from 41 species of the evergreen broadleaf forests of the South Central Coastal region of Viet Nam. Different power models that used diameter at breast height (DBH), tree height (H), wood density (WD), and crown area (CA) as covariates to predict aboveground biomass (AGB) were evaluated. Best models were selected based on the coefficient of determination (R^2), the Akaike information criterion (AIC), and root mean square percent error (RMSE). AGB was strongly related to four covariates - DBH, H, WD, and CA. While seldom mentioned in the existing literature, CA improved the accuracy of the AGB estimation. Accuracy of the selected models was validated using the random validation dataset and the model with four explanatory variables ($AGB = a \times (DBH^2HWD)^b \times CA^c$) had the lowest mean absolute percent error of 16.9%. Using local data, a simple power model based on DBH only ($AGB = a \times DBH^b$) produced higher accuracy than the generic pantropical models that used up to three variables.

1. Introduction

Accurate biomass estimation is critical component in quantifying forest carbon stocks and sequestration rates and assessing potential impacts due to climate change. Biomass equations will remain a key component of future carbon measurements and estimation (Temesgen et al., 2015). As part of the country's effort to engage and prepare for REDD+ (reducing emissions from deforestation and forest degradation) program, biomass equations are being examined in Viet Nam. Allometric equations for converting national forest inventory data to biomass and converting it to forest carbon stock estimates were proposed for each of the main forest types and ecological regions of Viet Nam (Sola et al., 2014a, 2014b; Huy et al., 2012; Huy, 2014).

Broadly, allometry is the linear or non-linear correlation between increases in tree dimensions (Picard et al., 2012). The most important covariates for biomass equations are tree diameter at breast height (DBH) (Brown et al., 1989, 2001; Brown, 1997; Brown and Iverson, 1992), wood density (WD), and tree height (H) (Chave et al., 2005; Basuki et al., 2009; Ketterings et al., 2001). WD converts volume to weight and varies over a considerable range (factor 4) between species (Picard et al., 2012; Chave et al., 2006). As WD is often not measured in the field, averages at the species level can be associated with trees (Fayolle et al., 2013) and such data is often available in international databases (IPCC, 2006; Chave et al., 2009). Further database is found at http://db.worldagroforestry.org/wd. Furthermore, some authors suggested that crown diameter (CD) or crown area (CA) helps to improve accuracy and reliability of biomass estimates (Dietz and Kuyah, 2011; Henry et al., 2010). Numerous publications suggest power models for building allometric equations based on one or more variables (e.g. Pearson et al., 2007; Picard et al., 2015). Sometimes the second-order exponential function of parabola has been used (e.g. Brown et al., 1989; Brown, 1997). Basuki et al. (2009) used the logarithm model for dipterocarp forest biomass and compared with the higher-order parabolic functions of Brown et al. (1989) and Chave et al. (2005). Their results

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indicated that the transformed exponential function gives smaller deviation and higher reliability.

In countries with a limited tree flora, allometric functions are available for most of the tree species (Jenkins et al., 2003). For example, Jenkins et al. (2004) compiled 2640 DBH based allometric equations for predicting total and component biomass for tree species found in North America. Given the diversity of tropical forests, developing species-specific equations is not realistic and researchers have focused on multi-species models with larger sample sizes, e.g. Brown (1997) used 371 trees with DBH ranging from 5 cm to 148 cm and Chave et al. (2005) used 2410 trees with DBH ranging from 5 cm to 150 cm. These generic models provide valuable information for the tropical regions characterized by lack of data and difficulties in accessing it. These models, however, may face limitations and are potentially biased in some case where a particular ecosystem was not represented in the development of the generic models. Jara et al. (2015) and Chave et al. (2014) indicated that such generic equations might lead to systematic errors of up to 400% at the site level. Locally developed models may be a better alternative and are expected to provide less uncertainty than generic equations (Chave et al., 2014). Temesgen et al. (2007, 2015) suggested developing comprehensive biomass estimation methods that account for differences in site and stand density, and improve forest biomass modeling and validation at a range of spatial scales.

For natural forests, Huy and Anh (2008) conducted a preliminary study on CO_2 absorption capacity of evergreen broadleaf forests in the Central Highlands of Viet Nam. In preparation for the implementation of the UN-REDD+ program, biomass equations, common guidelines, and sets of biomass models are being developed for each ecoregion in Viet Nam (Sola et al., 2014a, 2014b). It has also been part of the development of database and guidelines for the use models in Viet Nam (Henry et al., 2015).

In this context, this study aims to develop and validate local allometric equations for evergreen broadleaf forests in the South Central Coastal ecoregion of Viet Nam, and compare them to the generic pantropical equations developed using data that do not include data from Viet Nam.

2. Materials and methods

2.1. Study site

This study was carried out in the evergreen broadleaf forests of the South Central Coastal region, which is one of the eight important agro-ecological regions in Viet Nam and has the highest rate of forest cover. Evergreen broadleaf forests are also common in all ecological zones surrounding the Central Highlands and in adjacent forest ecosystems of Cambodia and Laos.

Sample plots were located in Quang Nam Province (15°28′13.3″N to 15°28′16.1″N and 107°48′56.6″E to 107°48′59.6″E), at an elevation of 574–624 m.a.s.l. with slopes of 10–40°. The site soils are yellow brown, developed on ancient alluvium, with pH values 6.0–6.3 and soil depth layers greater than 100 cm. Mean annual precipitation is 3150–3500 mm with minimum and maximum precipitations 1857 mm and 5337 mm respectively. The average annual temperature is 21.8 °C, with an annual range between 16.0 °C and 39.4 °C. The location has two distinct seasons: the dry season from February to August and the rainy season from September to January. Average humidity is 90% and mean evaporation is 800 mm and fog usually occurs from November to February (Hydrometeorology Center in Central Viet Nam, 2012).

2.2. Sample plot design, tree selection, and measurement

This study was conducted in two sample plots of 1 ha (100 m × 100 m) that were each divided into 100 sub-plots of 10 m × 10 m. Within the plots, attributes measured were (i) plot location; (ii) stand information: forest types and status, canopy cover, numbers of vertical forest layer, and basal area (BA); (iii) topography: slope and location on the mountain; (iv) soil characteristics: pH, depth, and color; and (vi) standing trees measurements: species name (local and scientific), DBH (cm), and tree height (H, m) of all trees with DBH ⩾ 5 cm.

Within the one-ha sample plots, the number of trees sampled was determined by the ratio of trees in each diameter class, while for the larger diameter classes (i.e., DBH ⩾ 45 cm) at least three trees were sampled. Fig. 1 shows the number of trees and basal area by DBH class in each of the inventory plot. The sample trees were also selected based on their dominance in the stand. A total of 110 trees, 55 from each plot, were sampled. Average DBH of the sample trees was 25.6 cm (range 4.9–87.7 cm) and average height was 17.5 m (range 4.7–41.4 m). The distribution of DBH and H of the destructively sampled trees is shown in Fig. 2. Table 1 shows a summary for each of the predictors and the response variables of the destructive sample trees.

DBH, H, CD (m) (measuring in two cardinal directions – North-South and East-West), and species of each sample tree were recorded before the tree was felled. Tree height was re-measured after the sample trees were felled. The fresh-weight of tree components (leaves, branches and stem with bark) were also recorded in

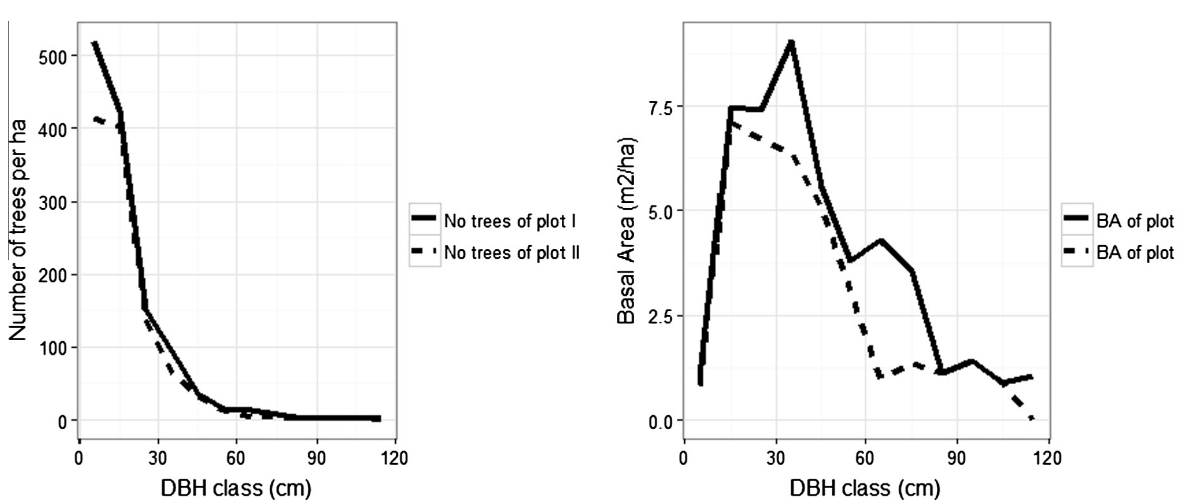

Fig. 1. Structure of evergreen broadleaf forests in the South Central Coastal region of Viet Nam.

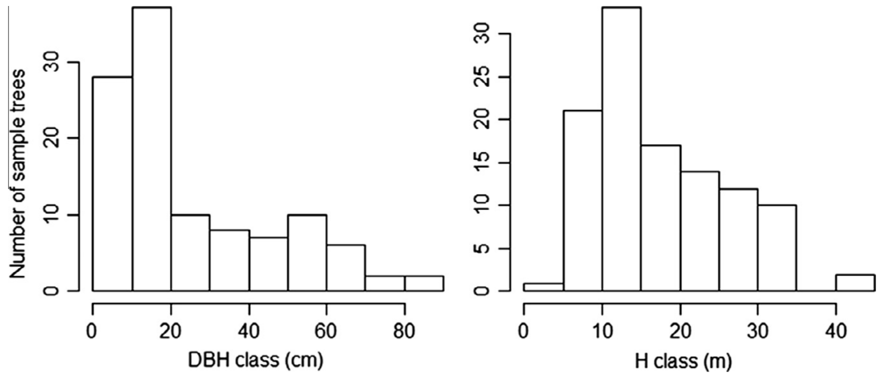

Fig. 2. Distribution of DBH and height of destructively sampled trees.

the field. Stems of sample trees were sectioned into five logs of equal length and the diameter with and without bark at the base of each log was recorded. Samples of four biomass components were brought to lab for dry weight, fresh to dry weight ratio, and wood density calculation. Wood and bark samples were approximately 500 g and 300 g and were taken from each of the five stem sections. Branch samples were approximately 500 g and obtained from three positions on branch. Approximately 300 g of leaves were also taken to lab from each sample branch.

2.3. Laboratory measurements

When in the lab, the fresh volume of wood and bark samples was obtained using the water displacement method. All the samples were then chipped into small pieces and dried at 105 °C until constant weight was achieved. WD (g/cm^3) of the sample was obtained as the ratio between dry weight and green volume of each sample. WD of sample tree was obtained as the average density of wood samples taken from five stem segments. Volume and density of bark samples were also obtained in similar fashion. Table 2 shows the list of species, average and standard deviation of WD, and the number of trees sampled in each species.

2.4. Compilation of data

Volume of five stem segments with and without bark was calculated using Huber's formula (Chapman, 1921). Fresh bark volume of sample trees V_{ba} (m^3) was obtained as the difference between volume of stem segments with bark and volume without bark whereas the fresh bark density (df_{ba} g/cm^3) was obtained as the average density of bark samples. The fresh biomass of bark in each tree (Bf_{ba} kg/tree) was computed as the product of df_{ba} and bark volume V_{ba} (m^3/tree) as follows:

$$Bf_{ba} = df_{ba} \times V_{ba} \times 10^3 \tag{1}$$

Fresh biomass of stem wood was then obtained by subtracting fresh bark biomass from the fresh weight of stem. Dry biomass of each tree component was calculated as its fresh weight multiplied by the fresh-to-dry ratio. Aboveground biomass (AGB) of each tree (kg) is the sum of biomass of stem (B_{st}), biomass of branches (B_{br}), biomass of leaves (B_l), biomass of bark (B_{ba}) and biomass of stump (B_{stu}). Crown area (m^2), one of the explanatory variable in our equations was computed using Eq. (2).

$$CA = \pi \frac{CD^2}{4} \tag{2}$$

where CD is average crown diameter (m).

2.5. Model fitting and selection

We used DBH, H, WD, and CA as covariates to predict AGB in this study. A large range of models such as power, logarithm, and second-order exponential function of parabola were tested. However, based on our exploratory results, we mainly used various power models as final biomass equations in this study. The list of models tested for each group of covariates or combination of covariates are given in Table 3. In the models, the combination of DBH and H (DBH^2H (m^3) = $\left(\frac{DBH}{100}\right)^2 \times H$) is surrogate of volume and the combination of DBH, H and WD (DBH^2HWD (kg) = $DBH^2H \times WD \times 1000$) is surrogate of biomass. Modeling was performed in statistical software R (R Core Team 2015). We also examined log-linear and weighted non-linear models using Furnival index (1961) that account for different response variable (i.e. AGB vs. log(AGB) (Jayaraman, 1999)). The model which has a lower Furnival index and so is to be preferred. To account for heteroscedasticity in residuals, we fit weight non-linear models. When the models to be compared do not have the same form of the dependent variable, Furnival index (1961) is invariably used. Best models were also selected based on coefficient of determination (R^2), Akaike information criterion (AIC), and root mean square percent error (RMSE), a measure of accuracy of the prediction (Temesgen et al., 2014).

$$RMSE\ (\%) = 100\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \tag{3}$$

where n is number of trees used for model development, and y_i and $\hat{y}_i$ are observed and predicted biomass in kg.

2.6. Model validation and comparison to pantropical models

All selected models in this study were validated and compared to each other and to generic models in term of bias (%), RMSE (%), and mean absolute percent error (MAPE, %) - average deviation percent (Mayer and Butler, 1993; Chave et al., 2005; Basuki et al., 2009). Smaller values of these indicators are preferred. Eighty percent of the data, equivalently 88 trees, were used to develop allometric equations and remaining 20% data, equivalently 22 trees, were used for model validation. The cross-validation statistics were computed for each realization of randomly selected data, and averaged over the 200 realizations (Temesgen et al., 2014).

$$Bias\ (\%) = \frac{1}{R}\sum_{r=1}^{R}\frac{100}{n}\sum_{i=1}^{n}\frac{y_i - \hat{y}_i}{y_i} \tag{4}$$

$$RMSE\ (\%) = \frac{1}{R}\sum_{r=1}^{R}100\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \tag{5}$$

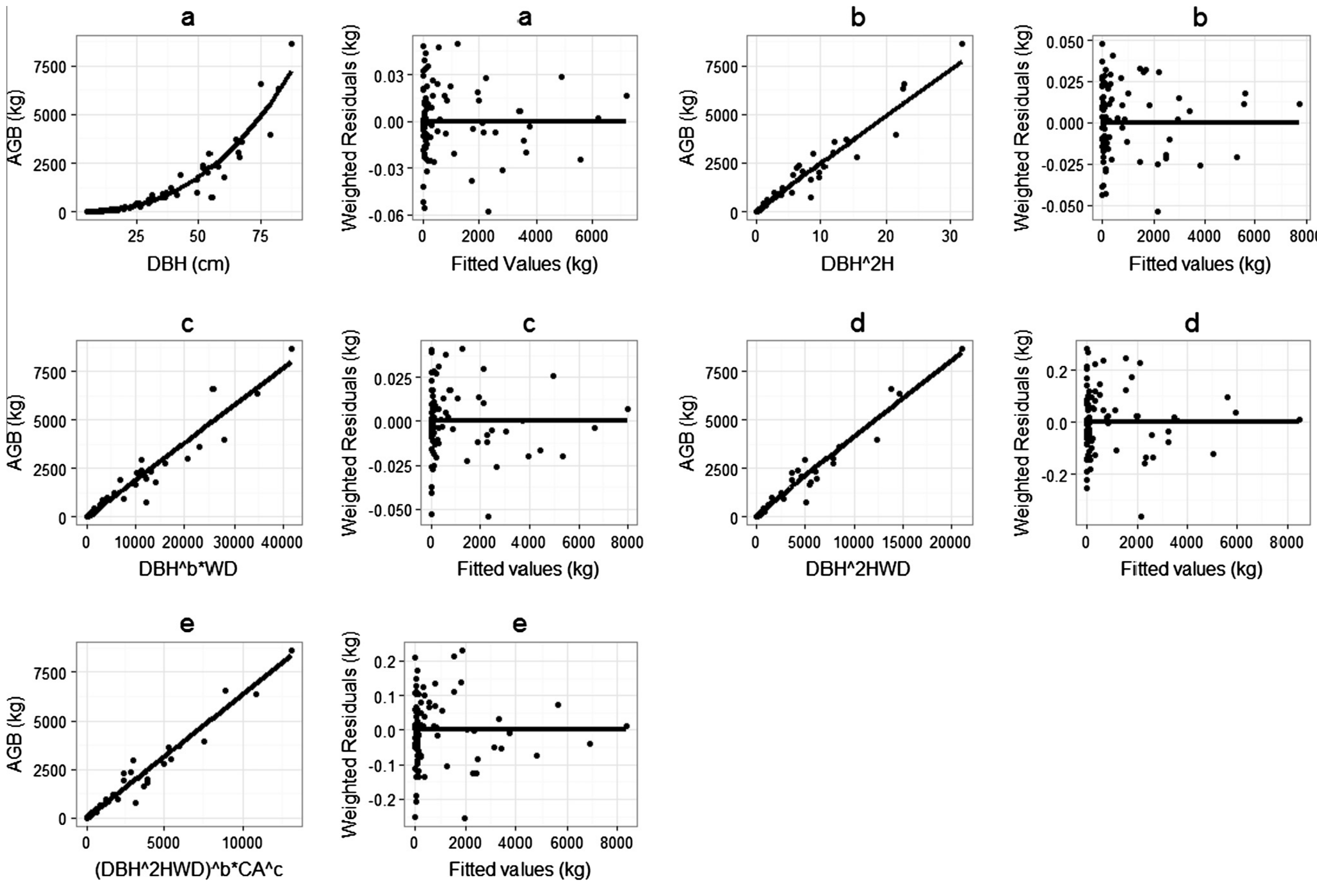

Fig. 3. Plots of fitted versus observed total aboveground biomass and fitted values against weighted residuals obtained from the selected models (Eqs. (7)–(11), figures a–e respectively).

Table 1
Summary for each of the predictors and the response variables of the destructively sampled trees.

Summary	DBH (cm)	H (m)	WD (g/cm^3)	CA (m^2)	AGB (kg)
Min	4.9	4.7	0.430	0.79	5.9
Average	25.7	17.5	0.586	24.53	804.4
Max	87.7	41.4	0.712	201.06	8633.0
Standard deviation	21.2	8.6	0.052	31.86	1482.4

$$\text{MAPE } (\%) = \frac{1}{R}\sum_{r=1}^{R}\frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \tag{6}$$

where R is number of resampling (2 0 0); n is number of trees per resampling r, and y_i and $\hat{y}_i$ are observed and predicted biomass.

3. Results

The data set used to examine selected biomass equations covered a wide range of DBHs and heights (Table 1). There were substantial differences in the biomass estimates obtained using the local model and the regional models suggested by IPCC (2003) (Fig. 4).

Most of the models fitted using weighted nonlinear method had lower Furnival's Index and higher adjusted R^2 than those models performed by log transformation (Table 3). Hence, we used weighted nonlinear regression to fit the AGB models for all different covariates.

Table 4 shows the parameter estimates and indicators of model fit obtained by using models with different covariates to estimate AGB. Based on the AIC, RMSE and adjusted R^2 values and considering the plots of fitted values against their residuals (Fig. 3), following models for combination of covariates are selected:

$$AGB = 0.10419 \times DBH^{2.49145} \tag{7}$$

$$AGB = 266.858 \times DBH^2 H^{0.97233} \tag{8}$$

$$AGB = 0.18879 \times DBH^{2.47329} \times WD \tag{9}$$

$$AGB = 0.59831 \times (DBH^2 HWD)^{0.95979} \tag{10}$$

$$AGB = 0.60205 \times (DBH^2 HWD)^{0.88170} \times CA^{0.16834} \tag{11}$$

Bias, RMSE and MAPE were calculated to validate the selected models. Table 5 shows indicators of validation of the selected models for different combination of covariates. Bias of these models ranged from −6.4% to 1.9%, RMSE ranged from 21.1% to 25.6% and MAPE ranged from 16.9% to 22.1%. The performance statistics indicate that observed and predicted AGB values closely matches, indicating that the selected models are viable and reasonable (Fig. 4). Among the selected models, the model with four variables (DBH, H, WD, and CA, Eq. (11) had the lowest average MAPE of 16.9%. Fig. 5 shows histograms of MAPE of the selected models, Eqs. (7)–(11), over the 200 realizations of randomly selected validation data.

Table 2
Number of trees and their wood densities (average and standard deviation) by species destructively sampled in this study.

Species name	n	WD (g/cm^3)	
		Average	Standard deviation
Aglaia elaeagnoidea (A.Juss.) Benth.	1	0.485226	
Aglaia roxburghiana (Wight & Arn.) Miq.	4	0.582639	0.088617
Baccaurea ramiflora Lour.	1	0.603114	
Barringtonia racenmosa (L.) Spreng.	3	0.530579	0.032070
Calophyllum dryobalanoides Pierre	1	0.567293	
Camellia fleuryi (A.Chev.) Sealy	4	0.597433	0.063261
Canarium littorale Blume	7	0.625701	0.021078
Cinnamomum subavenium Miq.	1	0.626005	
Dillenia indica var. *aurea* (Sm.) Kuntze	4	0.530882	0.037693
Diospyros decandra Lour.	1	0.663821	
Diospyros pilosula (A.DC.) Wall. ex Hiern	3	0.624073	0.015169
Elaeocarpus kontumensis Gagnep.	3	0.583962	0.013265
Endospermum chinense Benth.	1	0.570248	
Garcinia hanburyi Hook.f.	2	0.694431	0.004850
Garcinia oliveri Pierre	2	0.627243	0.119455
Gardenia philastrei Pierre ex Pit.	1	0.565626	
Gironniera subaequalis Planch.	4	0.526131	0.039544
Horsfieldia amygdalina (Wall.) Warb.	1	0.564658	
Ilex annamensis Tardieu	1	0.581080	
Knema pierrei Warb.	4	0.597548	0.007611
Lepisanthes rubiginosa (Roxb.) Leenh.	2	0.605106	0.062757
Lithocarpus annamensis (Hickel & A. Camus) Barnett	7	0.579616	0.043851
Litsea baviensis var. *venulosa* H. Liu	1	0.514746	
Litsea elliptica Blume	1	0.582340	
Maclurodendron oligophlebium (Merr.) T.G. Hartley	3	0.524136	0.032941
Madhuca alpina (A.Chev. ex Lecomte) A.Chev.	3	0.630592	0.016732
Magnolia braianensis (Gagnep.) Figlar	3	0.598895	0.071790
Melanorrhea curtisii Oliv.	1	0.626371	
Melia azedarach L.	1	0.502230	
Nauclea orientalis (L.) L.	1	0.430500	
Polyalthia nemoralis Aug.DC.	6	0.591398	0.034286
Prunus ceylanica (Wight.) Miq.	1	0.589221	
Pterospermum diversifolium Blume	1	0.555701	
Sapium baccatum Roxb.	2	0.559810	0.021850
Scaphium lychnophorum (Hance) Pierre	8	0.593851	0.024956
Shorea farinosa C.E.C.Fisch.	7	0.611231	0.035526
Sterculia parviflora Roxb.	2	0.588855	0.078540
Styrax benzoin Dryand.	1	0.556764	
Syzygium levinei (Merr.) Merr.	8	0.596154	0.034810
Terminalia calamansanay Rolfe	1	0.573957	
Vitex sp.	1	0.523569	
Total/average	110	0.585753	0.051999

4. Discussion

4.1. Comparison of AGB estimations

AIC, RMSE and Adjusted-R^2 values were used as indicators to compare the performance of biomass models (Table 4). As expected, increasing the number of independent variables from one to four reduced the AIC values and RMSE of the AGB estimates. Tree height among diameter classes is affected by some factors such as biological characteristics of species and growing conditions. Therefore, adding height in the model improved the accuracy of the model. WD is considered as representative of species effect in biomass models (Picard et al., 2012). It is particularly important, as it allows the conversion of individual tree volume into biomass.

CA and branch biomass varied greatly due to morphological characteristics of each species. For instance, for trees with similar DBH, H, and WD, it is easy to assume the same average biomass of the stem, however the biomass of their branches and foliage may differ depending on site conditions and terrain that may affect morphology. As a result, the addition of the CA may improve the reliability of AGB estimates where the development of species-specific allometric equations is not a realistic option. The model with four explanatory variables DBH, H, WD, and CA (Eq. (11)) had the lowest AIC and RMSE and the highest adjusted R^2. This model has the potential to produce the highest reliability but a practical concern is that, with more variables, its application becomes more complex and costly.

The power equations with combination of covariates (e.g. Eqs. (8), (10) and (11)) are appropriate for biomass models and have smaller number of parameters. This result is consistent with the remarks made by Weiskittel et al. (2015) that highlighted the limitations of biomass equations that are simplistic in model forms and predictor variables are used.

4.2. Comparison of selected models with generic pantropical models

The selected equations were compared with the generic models that depended on same number of explanatory variables (Fig. 4). The DBH based model developed in this study was compared to the equations of Brown (1997) and IPCC (2003) that also depended only on DBH for tropical moist forests. Equations with two (DBH and WD) or three variables (DBH, H and WD) were compared to the equations published by Chave et al. (2005, 2014) developed for tropical forests in America, Asia, and Oceania with the same two or three variables.

With the same input variable or combination of variables, indicators bias, RMSE and MAPE of the models developed in this study were significantly lower than those of generic pantropical models. The one-variable (DBH based) model developed in this study reduced RMSE from 43.7% to 22.5% and MAPE was reduced by at least 19% compared to the one-variable models of Brown (1997) and IPCC (2003). With our three variable (DBH, H and WD) model, the MAPE was reduced by 8.4% compared to the three variable model of Chave et al. (2014) (Table 5). These results showed a significant improvement of accuracy when using eco-regional models compared to the generic models.

This finding is supported by Nelson et al. (1999) and Cairns et al. (2003) when they applied the generic equations to their data, the predicted values were over estimated. Basuki et al. (2009) compared the local AGB equations developed for dipterocarp forests in Indonesia to generic equations and showed that these local and generic equations differ substantially and that site specific equations must be considered to get a better estimation of biomass. When the equations of Chave et al. (2005) and Brown (1997) were applied to Basuki et al. (2009) data, the predicted values were over estimated.

We also observed that the accuracy of one variable DBH based model developed in this study was higher than generic models with up to three variables. For example, our DBH based model reduced MAPE by 11.5% and RMSE by 13.2% compared to the generic equation of Chave et al. (2014) that is based on DBH, H, and WD (Table 5). This suggests that, if we intend to set up generic models for tropical areas or for the whole country, these models will need to include random effects for each ecological region.

While, we compared models developed in this study with the generic pantropical models, their coefficients are not directly comparable because of the model forms, except for the three variable model (Eq. (10)) and the Chave et al. (2014) equation. The exponent of our three variable model was similar to the exponent of Chave et al. (2014) equation (0.959790 vs. 0.976, respectively) but the scaling factor differed substantially, 0.598313 vs. 0.0673, respectively. One of the reasons for these differences could be the differences in wood densities.

The pantropical models suggested by IPCC (2003) resulted in large bias and RMSE in estimating AGB. This is a great concern

Table 3
Models tested in each group of input variables and comparison between log transformation and weighted nonlinear fitting by using Furnival's Index.

Input variables	Biomass equations	Model No.	Log transformation model		Weighted nonlinear model		
			Adj. R^2	FI	Weight variable	Adj. R^2	FI
DBH	$AGB = a \times DBH^b$	I	0.980	40.9	$1/DBH^k$	0.930	0.023
	$AGB = a + b \times DBH + c \times DBH^2$	II			$1/DBH^k$	0.885	0.020
	$AGB = a + b \times DBH + c \times DBH^2 + d \times DBH^3$	III			$1/DBH^k$	0.925	0.021
DBH and H	$AGB = a \times (DBH^2H)^b$	IV	0.984	36.9	$1/DBH^k$	0.946	0.021
	$AGB = a \times DBH^b \times H^c$	V	0.985	36.0	$1/DBH^k$	0.944	0.018
DBH and WD	$AGB = a \times DBH^b \times WD$	VI			$1/DBH^k$	0.941	0.019
	$AGB = a \times DBH^b \times WD^c$	VII	0.984	36.4	$1/DBH^k$	0.940	0.018
DBH, H, and WD	$AGB = a \times (DBH^2HWD)^b$	VIII	0.987	33.3	$1/(DBH^2HWD)^k$	0.962	0.122
	$AGB = a \times DBH^b \times H^c \times WD^d$	IX	0.988	31.7	$1/DBH^k$	0.957	0.015
DBH, H, WD, and CA	$AGB = a \times (DBH^2HWD)^b \times CA^c$	X	0.988	31.3	$1/(DBH^2HWD)^k$	0.963	0.096
	$AGB = a \times DBH^b \times H^c \times WD^d \times CA^e$	XI	0.989	30.7	$1/DBH^k$	0.959	0.012

NB: FI is Furnival's Index. Group of input variables were calculated as follows: DBH^2H (m^3) = (DBH (cm)/100)^2 × H (m) and DBH^2HWD (kg) = DBH^2H (m^3) × WD (g/cm^3) × 1000.

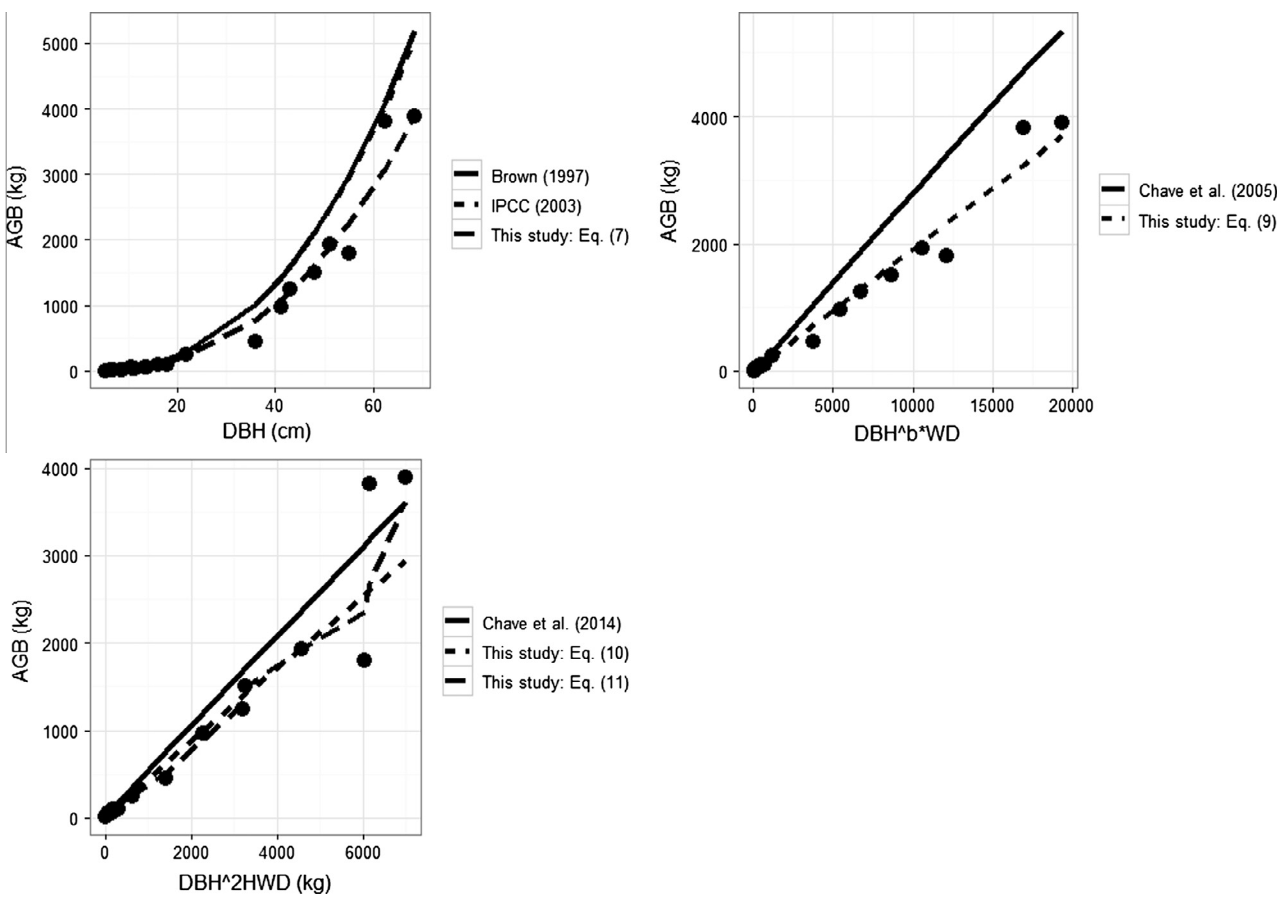

Fig. 4. Graphs of the validation data and predicted values obtained by using models developed in this study and generic pantropical allometric equations.

for scientists, citizens, and policy makers who are charged to develop and implement policies and mechanisms to assist in mitigating climate change, in setting carbon inventories for National Greenhouse Gas Inventory and for Clean Development Mechanism projects. The revised local biomass equation will improve biomass and carbon estimates which are key components for REDD+ and other projects in Viet Nam.

5. Conclusion

All covariates - DBH, H, WD, and CA were strongly related to AGB. DBH and H represent the relationship between the tree volume with biomass, while WD and CA represent the biological characteristics of the species and shape of canopy. The increase of independent variables in biomass equations from one to four

Table 4
Parameter estimates and indicators of model fit obtained by using different input variables to estimate AGB. Parameters of all the models were significant at 0.05 level of significance.

Model No.	Parameter estimates					AIC	Adjusted R^2	RMSE (%)
	a	*b*	*c*	*d*	*e*			
I	0.10419	2.491453				902.9	0.930	38.7
II	25.15789	−7.717925	0.82106			911.1	0.885	35.8
III	15.90167	−4.926814	0.59812	0.00409		917.0	0.925	37.1
IV	266.858	0.972330				884.5	0.946	31.6
V	0.05054	2.126979	0.64600			886.4	0.944	32.7
VI	0.18879	2.473292				880.8	0.941	35.6
VII	0.22885	2.466907	1.33120			887.2	0.940	35.0
VIII	0.59831	0.95979				871.5	0.962	29.5
IX	0.11198	2.150328	0.57042	1.21384		870.4	0.957	29.8
X	0.60205	0.881696	0.16834			865.3	0.963	27.2
XI	0.11494	1.968087	0.63262	1.16550	0.117818	874.3	0.959	27.9

Table 5
Validation of the selected models and comparison to pantropical models (N = 22 trees by splitting randomly 200 times). The cross-validation statistics were computed for each realization of randomly validation data, and averaged over the 200 realizations.

Models	Equation	Bias (%)	RMSE (%)	MAPE (%)
DBH				
Brown (1997)	$AGB = exp(-2.134 + 2.530 \times ln(DBH))$	−33.4	43.6	36.9
IPCC (2003)	$AGB = exp(-2.289 + 2.649 \times ln(DBH) - 0.021 \times (ln(DBH))^2)$	−33.4	43.7	36.9
Eq. (7)	$AGB = 0.104189 \times DBH^{2.491453}$	−4.6	22.5	17.9
DBH, H				
Eq. (8)	$AGB = 266.858 \times (DBH^2H)^{0.97233}$	1.9	25.6	22.1
DBH, WD				
Chave et al. (2005)	$AGB = WD \times exp(-1.499 + 2.148 \times ln(DBH) + 0.207 \times (ln(DBH))^2 - 0.0281 \times (ln(DBH))^3)$	−39.3	51.0	43.3
Eq. (9)	$AGB = 0.188791 \times DBH^{2.473292} \times WD$	−6.4	21.7	17.5
DBH, H, WD				
Chave et al. (2014)	$AGB = 0.0673 \times (WD \times DBH^2 \times H)^{0.976}$	−21.0	35.7	29.4
Eq. (10)	$AGB = 0.598313 \times (DBH^2HWD)^{0.959790}$	−3.2	25.0	21.0
DBH, H, WD, CA				
Eq. (11)	$AGB = 0.602051 \times (DBH^2HWD)^{0.881696} \times CA^{0.168337}$	−4.1	21.1	16.9

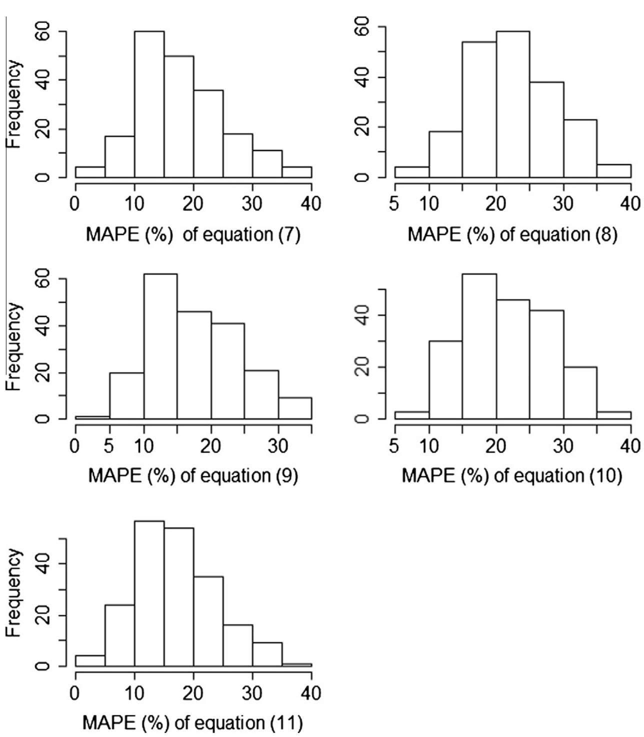

Fig. 5. Histogram of mean absolute percent error (MAPE) of the selected models (Eqs. (7)–(11)) over the 200 realizations of randomly selected validation dataset.

reduces the uncertainty of the estimates. The variable CA would be important to enhance the accuracy of the AGB estimation, while this variable has been seldom mentioned in existing publications. The variable CA is simple to measure and will not significantly impact surveying costs.

Combinations of covariates for biomass models, such as DBH^2H and DBH^2HWD which are surrogates of the tree volume and biomass respectively are more appropriate than using such variables separately. The power models such as $AGB = a \times DBH^b$ or the one that uses the combination of covariates such as $AGB = a \times (DBH^2H)^b$, $AGB = a \times DBH^b \times WD$, $AGB = a \times (DBH^2 \ HWD)^b$, or $AGB = a \times (DBH^2HWD)^b CA^c$ are appropriate for biomass estimation.

The AGB estimates obtained by using the selected models developed in this study closely matches with the observed biomass of randomly selected validation data, and the model with four explanatory variables (DBH, H, WD, and CA) had the lowest MAPE of 16.9%. The local model with single variable (DBH only) has higher reliability than generic models with up to three variables. The existing pantropical models overestimated the AGB for the random validation dataset. Therefore, national and pantropical models should be developed, with random effects of ecological factors, forest types, and regions or calibrated for local use.

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