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Allometric equations for estimating tree aboveground biomass in evergreen broadleaf forests of Viet Nam

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ABSTRACT

For mitigating climate change through carbon sequestration and for reporting, Viet Nam needs to develop biomass equations at a national scale. These equations need to be accurate and provide quantifiable uncertainty. Using data from 968 trees across five ecoregions of Viet Nam, we developed a set of models to estimate tree aboveground biomass (*AGB*) in evergreen broadleaf forests (EBLF) at the national level. Diameter at breast height (*DBH*), tree height (*H*), wood density (*WD*), and combination of these three tree characteristics were used as covariates of the biomass models. Effect of ecoregion, wood density, plant family on *AGB* were examined. Best models were selected based on AIC, Adjusted R^2, and visual interpretation of model diagnostics. Cross-validation statistics of percent bias, root mean square percentage error (RMSPE), and mean absolute percent error (MAPE) were computed by randomly splitting data 200 times into model development (80%) and validation (20%) datasets and averaging over the 200 realizations. Effects models were used, the best results were obtained by using a combined variable (DBH^2HWD (kg) = (DBH (cm)/100)$^2 \times H$ (m) $\times WD$ (g/cm^3) $\times$ 1000) model $AGB = a \times (DBH^2HWD)^b$. Including a categorical *WD* variable as a random effect reduced AIC, percent bias, RMSPE, MAPE of models $AGB = a \times DBH^b$ and $AGB = a \times (DBH^2H)^b$; ecoregion as a random effect reduced the AIC of models $AGB = DBH^b \times WD$, $AGB = a \times (DBH^2H)^b$, and $AGB = a \times (DBH^2HWD)^b$. For models that did not include *WD* variable, including plant family as a random effect reduced AIC, RMSE, and MAPE; recommendations are provided for models with specific parameters for main families and without *WD* if this variable is not available. The overall best model for estimating *AGB* was the equation form $AGB = a \times (DBH^2HWD)^b$ with ecoregion as a random effect.

1. Introduction

The management of forest ecosystems to mitigate climate change through CO_2 absorption deserves urgent attention from governments. The United Nations' Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) has been taking actions to help support this need in developing countries and Viet Nam since 2009. The Intergovernmental Panel on Climate Change (IPCC) has also provided guidelines for measuring and monitoring forest carbon (IPCC, 1996, 2003, 2006). However, there is still a need in Viet Nam for national scale models that can provide accurate estimates of biomass and carbon, and produce accurate emission factors.

Due to the diverse nature of tropical forests, the development of species-specific equations is not realistic and researchers have instead commonly focused on generic multi-species models (e.g. Brown et al., 1989; Brown and Iverson, 1992; Brown, 1997; Brown et al., 2001; Ketterings et al., 2001; Basuki et al., 2009; Chave et al., 2005, 2014). However, available models typically do not incorporate the distinction of forest type or ecoregion, nor have they been evaluated for their reliability in evergreen broadleaf forests (EBLF) of Viet Nam, the primary cover type of the country's natural forest spanning 14.2 million hectares (JICA and VNFOREST, 2012). These generic models provide valuable

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information for the tropics but may be biased in cases where a particular ecosystem, such as EBLF, was not represented in the development of such models (Jara et al., 2015). Therefore, developing models for comprehensive biomass estimation that consider differences in forest type or ecoregion is necessary (Temesgen et al., 2015).

Few allometric equations were developed in Viet Nam prior to the implementation of the UN-REDD programme (UN-REDD, 2011). However, as part of the country's effort to engage and prepare for the UN-REDD programme, biomass equations are now being explored. Allometric equations for converting national forest inventory data to biomass and forest carbon stock estimates have been proposed for the main forest types and ecological regions of Viet Nam (Sola et al., 2014a,b; Huy et al., 2013; Huy, 2014; Huy et al., 2016a,b). This study improves and updates national scale allometric equations for estimating AGB in EBLF of Viet Nam by including additional data collected by Huy et al. (2013) from the Central Highlands ecoregion and by improving the methods used to estimate model parameters. We further analyzed this data to increase the reliability of biomass estimates for different forest conditions in Viet Nam by considering the effect of ecoregion, plant family, and wood density (*WD*) on *AGB*, and evaluating the reliability and accuracy of the selected models examined in this study.

2. Methodology

2.1. Study sites

Five of Viet Nam's eight agro-ecological zones, or ecoregions, contain most of the country's forest cover: the central highlands (CH), north central coastal (NCC), northeast (NE), south central coastal (SCC), and southeast (SE). Therefore, this study focused on estimating biomass of EBLF in the five representative ecoregions of Viet Nam (Fig. 1). These ecoregions span a range of ecological, climatic, and structural site characteristics (Table 1).

Elevation of EBLF in these ecoregions ranges from 197 to 1068 m with up to 40° slopes in some areas. Mean annual rainfall is between 1055 and 2500 mm with the dry seasons lasting 3 and 5 months and mean annual temperature ranging from 16.9 to 25.0 °C. The EBLF in Viet Nam is distributed primarily on a soil type of sedimentary rock, crystalline schist, igneous rock, or some combination thereof. Stand density can range from 370 to 3300 trees per ha (DBH > 5 cm) and BA can range from 9.2 to 48.9 m^2 per ha (This study; Hijmans et al., 2005; Fischer et al., 2008).

2.2. Sampling design and data collection

Most of the data used in this study was collected with the support of Vietnam UN-REDD Phase I Programme (Phuong et al., 2012b). Additional data for the Central Highlands ecoregion was collected with support from the Ministry of Education and Training (Huy et al., 2013).

A total of 14 1-ha (100 × 100 m) sample plots were established across the five ecoregions. A total of 26 0.2-ha (20 × 100 m) were added for the Central Highlands where EBLF mainly covers in the country. Within a plot, species and diameter at breast height (DBH) was recorded for all trees greater than 5 cm in *DBH*. Sample trees were selected from each plot and destructively sampled for *AGB* measurements. Sample tree selection focused on the main species. A total of 968 trees were destructively sampled with the *DBH* of sampled trees ranging from 4.7 to 87.7 cm and with heights (*H*) of 3.9–41.4 m. Table 2 shows the number of trees sampled by ecoregion and main plant family.

Fresh biomass of stems, branches, and new and old leaves were measured in the field. Samples from stem, branches, and new and old leaves were taken to obtain the fresh-to-dry mass ratio of each tree component and to calculate the total *AGB*. Dry weight of wood samples was obtained by drying them in ovens until a constant weight was reached. *WD* was then calculated as the ratio of dry mass to the volume of wood samples taken from every one-fourth or one-fifth of stem length (Phuong et al., 2012a). Fig. 2 shows *AGB* against *DBH* of all destructively sampled trees by ecoregion and main plant family. Table 3 shows a summary for each of the predictors and the response variables of the destructive sample trees.

2.3. Model development

Commonly used covariates for estimating *AGB* models are *DBH*, *WD*, and *H*. These easily measurable dendrometric variables have been related to *AGB* through a variety of model forms such as power, logarithmic, and exponential functions (Brown, 1997; Ketterings et al., 2001; Jenkins et al., 2003, 2004; IPCC, 2003; Basuki et al., 2009; Dietz and Kuyah, 2011; Johannes and Shem, 2011; Chave et al., 2005, 2014; Henry et al., 2010, 2015; Huy et al., 2016a,b). The power models are very common and are fitted either as linear models after logarithmic transformation or as non-linear models (Brown, 1997; Chave et al., 2014; Basuki et al., 2009). As biomass models are generally heteroscedastic, the logarithmic transformation can help meet the assumption of error variance homogeneity, but it can also introduce transformation bias. On the other hand, the use of non-linear models allows for flexibility in model forms and can account for heterogeneity of errors (Davidian and Giltinan, 1995).

Large scale biomass estimation requires generic models that account for the variability in biomass due to geographic locations. However, traditionally developed fixed effects models do not take into consideration the grouping of the data by locations. Mixed effect models are appropriate when data are grouped and have errors that are correlated and/or have unequal variances (Bates, 2010; Pinheiro et al., 2014). Our national scale biomass dataset has a location grouping variable of ecoregion. Therefore we used weighted non-linear mixed effects models to develop national scale biomass equations. The models were fit based on the maximum likelihood procedure in R statistical software using the nlme package (Picard et al., 2012; Pinheiro et al., 2014) and model diagnostics were conducted using the ggplot2 package (Wickham and Chang, 2013). The general form of the *AGB* model was:

$$\mathrm{Y}_{ij} = (\alpha + a_i) \times \mathrm{X}_{ij}^{(\beta + b_i)} + \varepsilon_{ij} \tag{1}$$

$$\varepsilon_{ij} \sim iid\,\mathcal{N}(0, \sigma^2) \tag{2}$$

$$a_i \sim iid\,\mathcal{N}(0, \sigma_a^2) \tag{3}$$

$$b_i \sim iid\,\mathcal{N}(0, \sigma_b^2) \tag{4}$$

where Y_{ij} is the *ABG* (kg) for the *j*th tree from the *i*th class of a variable; α and β are the fixed effect parameters of the model; a_i and b_i are parameters associated with *i*th class of a variable; X_{ij} is the covariate *DBH* (cm), *H* (m), *WD* (g/cm^3), DBH^2H (m^3), or DBH^2HWD (kg) for the *j*th tree in *i*th class of a variable; and ε_{ij} is the random error associated with the *j*th tree from the *i*th class of a variables. The independent combination variables DBH^2H and DBH^2HWD are approximations of volume and AGB, respectively, and were calculated as follows:

$$DBH^2H = \left(\frac{DBH}{100}\right)^2 \times H \tag{5}$$

$$DBH^2HWD = DBH^2H \times WD \times 1000 \tag{6}$$

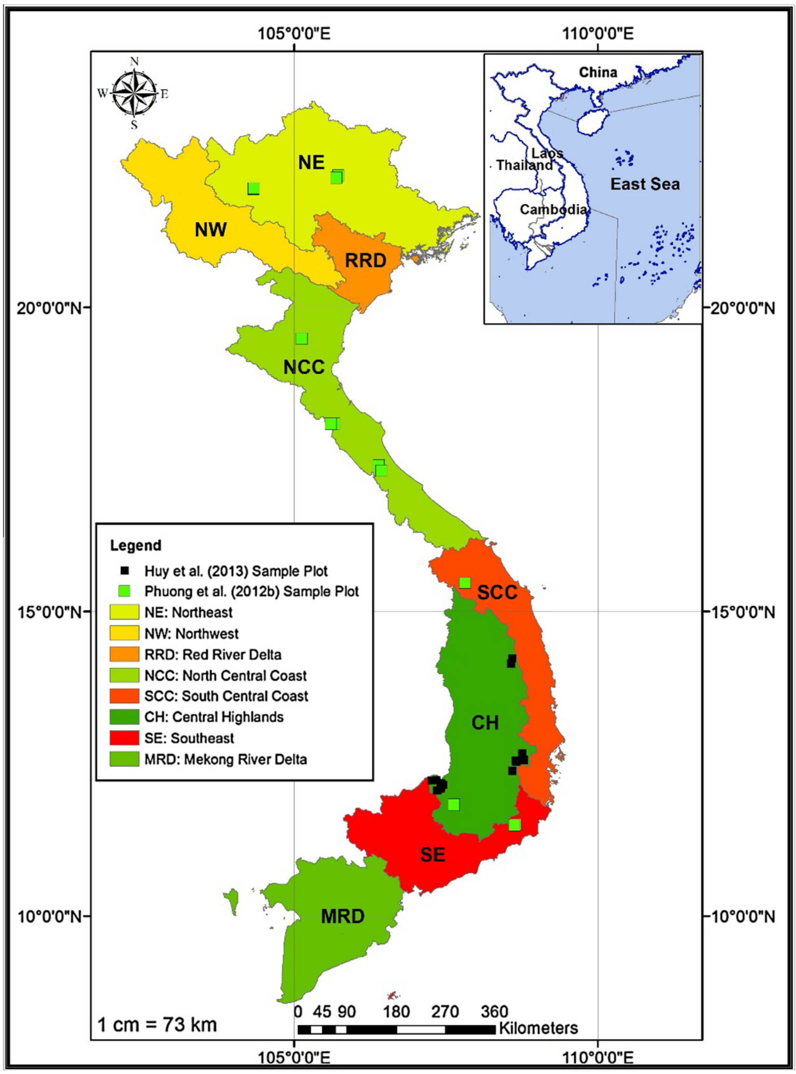

Fig. 1. Ecoregions in Viet Nam and sample plot locations (black, Huy et al., 2013; green, Phuong et al., 2012b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Ecoregion characteristics for EBLF of sample plots including elevation (m), slope (degrees), mean annual rainfall (Rain mm), dry season length (Dry, months), mean annual temperature (Temp, °C), soil type, stand density (trees per ha with *DBH* > 5 cm), and basal area (*BA*; m^2 per ha with *DBH* > 5 cm).

Ecoregion	Elevation	Slope	Rain	Dry	Temp	Soil	Density	BA
CH	377–1068	0–36	2100–2500	3	22.2–25.0	S	370–3300	9.2–48.9
NCC	197–430	0–28	1418–2262	3	21.9–24.8	S, C	476–1312	10.1–39.7
NE	580–750	28–32	1678–1908	5	16.9–21.0	C, I	418–999	17.8–25.5
SCC	574–624	10–40	2252	3	23.5	C	1076–1267	34.5–48.3
SE	320–340	15	1055–1068	5	24.2–24.5	S	791–924	37.8–48.3

Note: For Ecoregion, CH: Central Highland; NCC: North Central Coastal; NE: North East; SCC: South Central Coastal; SE: South East. For Soil type, S: Sedimentary rock, C: Crystalline schist, and I: Igneous rock. (This study; Hijmans et al., 2005; Fischer et al., 2008).

Preliminary analysis indicated that the variance of residuals tended to increase with increasing diameters in all *AGB* models. Therefore the covariance structure of the residuals was modeled with a power variance function to account for heteroscedasticity and improve parameter estimation. The variance function was defined as:

$$\mathrm{Var}(\varepsilon_{ij}) = \widehat{\sigma^2}(v_{ij})^{2k} \quad (7)$$

where ε_{ij} is as defined before; $\widehat{\sigma^2}$ is the residual sum of squares; v_{ij} is the weighting variable (*DBH*, DBH^2H or DBH^2HWD in this study) associated with the *j*th tree from the *i*th class of the random effect; and *k* is the variance function coefficient.

While random effects of other ecological, climatic, taxonomic, and stand characteristic factors were examined, many variables that could be used as surrogates for ecoregion, plant family, or *WD* have limited used or have difficulty in using or applying them. For example, dry season length, mean annual temperature, or mean annual precipitation are temporally and maybe effected by climate change and lead to mixed effects models that could be unreliable into the future. Some factors such as data on soil type can be difficult or costly to obtain, making their inclusion in mod-

Table 2
Number of trees destructively sampled from the five ecoregions and the nine main plant family groups.

Plant family	Ecoregion					Total
	CH	NCC	NE	SCC	SE	
Dipterocarpaceae	3	29	19	7	27	85
Euphorbiaceae	10	32	15	4		61
Fagaceae	29	25	24	7		85
Lauraceae	21	25	30	3		79
Leguminosae	1	34	19		19	73
Meliaceae	12	6	6	6		30
Myrtaceae	27	11	7	8	4	57
Ulmaceae	5	15	8	4		32
Others	114	134	87	71	60	466
Total	222	311	215	110	110	968

Note: CH: Central Highland; NCC: North Central Coastal; NE: North East; SCC: South Central Coastal; SE: South East.

els impractical for applied uses. Ecoregion is a useful grouping variable as it incorporates many ecological and climatic factors that likely affect *AGB*. Plant family and *WD* are also variables that are closely tied to *AGB* and are more easily obtained. Therefore, only ecoregion, plant family, and *WD* class were examined as potential random effects that may influence the allometric relationship between dendrometric variables and *AGB*.

Random effects of ecoregion, plant family, and *WD* on model parameters were tested to evaluate their influence in the allometric relationship. Ecoregion at five levels (NE, NCC, CH, SCC, SE) represented the influence of ecological and climatic factors on *AGB*. Nine main plant family groups were identified from the sample trees (Dipterocarpaceae, Euphorbiaceae, Fagaceae, Lauraceae, Leguminosae, Meliaceae, Myrtaceae, Ulmaceae, and other). Main plant family also represented an ecological influence on *AGB* and each level of plant family had at least 30 sample trees. While *WD* was used as a potential covariate to the *AGB* models, the effect of *WD* class was also examined for equations not explicitly incorporating *WD* as a fixed effect. Three *WD* classes were formed ($\leqslant$0.40; 0.41–0.60; >0.60) and represented a combination of ecological, climatic, and stand characteristic influences on *AGB*.

2.4. Model selection and validation

Modeling *AGB* with *DBH* and *H* as *f*(*DBH*, *H*), for example, as opposed to $f(DBH^2H)$ could increase model flexibility by allowing exponents on the covariates of *DBH* and *H* to vary; however doing so increases the number of parameters that need to be estimated. Therefore, for each combination of covariates (*DBH; DBH* and H; *DBH* and *WD; DBH*, *H*, and *WD*), fixed effect models were fit and the best model forms selected. The model forms were then evaluated based on diagnostic plots, AIC, Adjusted R^2, and the significance of parameters. If models had similar values for AIC, the selection among models was made based on the principle of model parsimony. After the best fixed effects model forms were selected for each combination of covariates, new mixed effects models incorporating the random effect of ecoregion, plant family, and WD class were examined.

The dataset of 968 sample trees was randomly split into model development (80%; 775 trees) and validation (20%; 193 trees) data and the process was repeated 200 times. Validation statistics were calculated for all selected fixed effects models and mixed effect models in this study. Models were compared in terms of percent bias, root mean square percentage error (RMSPE), and mean absolute percent error (MAPE) (Swanson et al., 2011). Validation statistics were computed for each realization of randomly selected data and then averaged over the 200 realizations (Temesgen et al., 2014).

$$\text{Percent Bias} = \frac{100}{R}\sum_{r=1}^{R}\sum_{i=1}^{n_r}\left[\frac{y_{ri}-\hat{y}_{ri}}{y_{ri}}\right]\Big/ n_r \tag{8}$$

$$\text{RMSPE} = \frac{100}{R}\sum_{r=1}^{R}\sqrt{\sum_{i=1}^{n_r}\left(\frac{y_{ri}-\hat{y}_{ri}}{y_{ri}}\right)^2\Big/ n_r} \tag{9}$$

$$\text{MAPE} = \frac{100}{R}\sum_{r=1}^{R}\sum_{i=1}^{n_r}\left[\frac{|y_{ri}-\widehat{y_{ri}}|}{y_{ri}}\right]\Big/ n_r \tag{10}$$

where R is the number of realizations (200); n_r is the number of trees per realization r; and y_{ri} and $\hat{y}_{ri}$ are the observed and predicted *AGB* (kg) for the *i*th tree in realization *r*, respectively. After validating each model, final estimates of model parameters and their standard errors are provided using the entire dataset.

3. Results

3.1. Model AGB = f(DBH)

A power model of the form $AGB = a \times DBH^b$ was used to develop a model with *DBH* as the only covariate. Random effects were tested on the power model and compared to the fixed effect model. Fit statistics and validation statistics for the resulting mixed effects, fixed effect, and selected models are shown in Table 4.

Compared to the fixed effect model, including *WD* as a random effect resulted in the greatest increase in adjusted R^2 and the greatest reduction of AIC, percent bias, RMSPE, and MAPE. While adding plant family as a random effect also improved all fit and validation statistics, there was not a substantial difference between parameter estimates for the mixed and fixed models (Table 5). Compared to the fixed effect model that used *DBH* as the only covariate (Table 5), ecoregion as a random effect did not improve fit statistics and did not substantially change parameter estimates.

The mixed effects model incorporating *WD* class as a random effect was selected as the best mixed model for the *DBH* only model form, as including *WD* class resulted in substantial changes in model parameters once the models were fit with the entire dataset. Therefore, *AGB* in EBLF of Viet Nam can be calculated with or without the random effect of *WD* using the equations and parameter estimates provided in Table 5. Final plots of *DBH* against *AGB* for fitted and predicted curves with *WD* class as a random effect are displayed in Fig. 3.

3.2. Model AGB = f(DBH, H)

For the power model incorporating *DBH* and *H* as covariates, the model forms $AGB = a \times DBH^bH^c$ and $AGB = a \times (DBH^2H)^b$ were

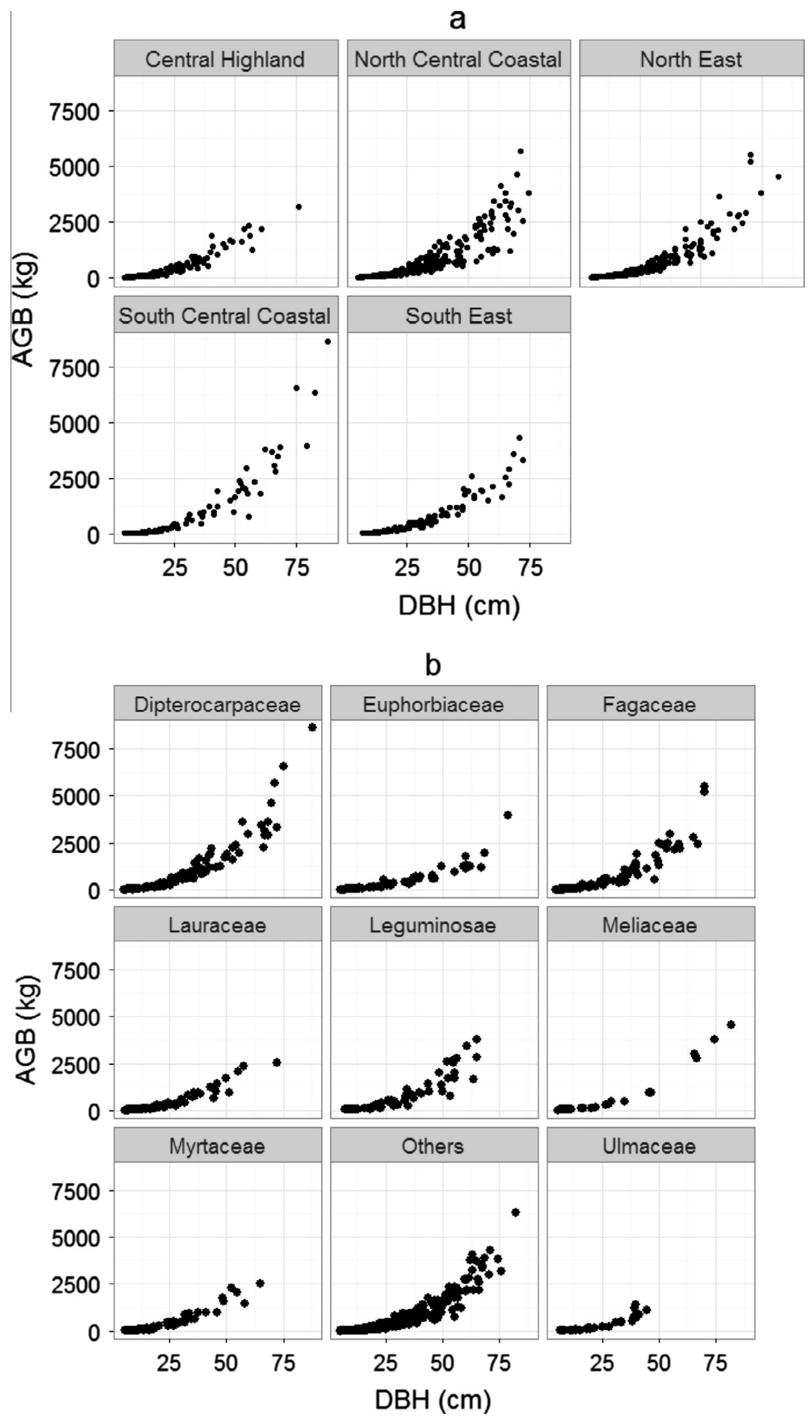

Fig. 2. Scatter diagrams of *AGB* vs. *DBH* of all destructively sampled trees by (a) ecoregion and (b) main plant family.

Table 3
Summary for each of the predictors and the response variables of the destructively sampled trees (n = 968).

Summary	*DBH* (cm)	*H* (m)	*WD* (g/cm^3)	*AGB* (kg)
Min	4.7	3.9	0.165	2.9
Average	25.0	17.4	0.547	553.7
Max	87.7	41.4	0.964	8633.0
Standard deviation	17.2	7.2	0.139	917.5

Table 4
Comparison and validation of different $AGB = f(DBH)$ models with and without random effects.

Model form	Random effect	Weight variable	AIC	Adj. R^2	RMSPE	Percent bias	MAPE
$AGB = a \times DBH^b$	None[a]	$1/DBH^k$	8425	0.886	42.1	−12.2	30.6
	Ecoregion		8433	0.885	41.3	−11.8	30.1
	WD class[a]		8292	0.923	31.7	−4.9	23.0
	Family		8395	0.894	40.8	−11.4	29.6

[a] Selected model.

Table 5
Final parameter estimates, standard errors, and sample size obtained using the entire dataset for fixed and mixed effects models of the form $AGB = a \times DBH^b$.

Random effect	Class	Parameters estimates		Standard error		Number of sample trees
		a	b	a	b	
None	–	0.128430	2.409074	0.005878	0.014967	968
Ecoregion	Central Highlands	0.128430	2.409076	0.005878	0.014967	222
	North Central Coastal	0.128430	2.409076	0.005878	0.014967	311
	Northeast	0.128430	2.409076	0.005878	0.014967	215
	South Central Coastal	0.128430	2.409076	0.005878	0.014967	110
	Southeast	0.128430	2.409076	0.005878	0.014967	110
Wood density	$\leqslant 0.40$ g/cm^3	0.106964	2.367518	0.001643	0.001580	151
	0.41–0.60 g/cm^3	0.127542	2.387309	0.000901	0.000867	502
	>0.60 g/cm^3	0.156034	2.414712	0.001138	0.001094	315
Plant family	Dipterocarpaceae	0.128430	2.409076	0.005878	0.014967	85
	Euphorbiaceae	0.128430	2.409076	0.005878	0.014967	61
	Fagaceae	0.128430	2.409076	0.005878	0.014967	85
	Lauraceae	0.128430	2.409076	0.005878	0.014967	79
	Leguminosae	0.128430	2.409076	0.005878	0.014967	73
	Meliaceae	0.128430	2.409076	0.005878	0.014967	30
	Myrtaceae	0.128430	2.409076	0.005878	0.014967	57
	Ulmaceae	0.128430	2.409076	0.005878	0.014967	32
	Others	0.128430	2.409076	0.005878	0.014967	466

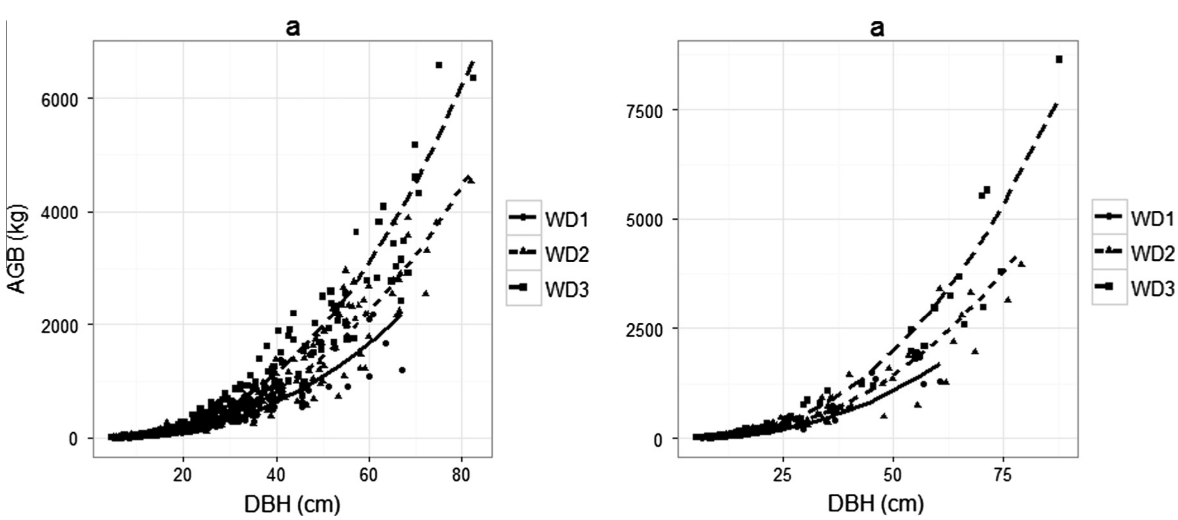

Fig. 3. Model $AGB = a \times DBH^b$ with random effect of *WD* class. The left is fitted values vs. the entire dataset for developing equations and the right is predicted values vs. one of the validation datasets.

Table 6
Comparison and validation of different $AGB = f(DBH, H)$ models with and without random effects.

Model form	Random effect	Weight variable	AIC	Adj. R^2	RMSPE	Percent bias	MAPE
$AGB = a \times (DBH^2H)^b$	None[a]	$1/DBH^k$	8342	0.896	36.6	−8.6	27.4
$AGB = a \times DBH^b \times H^c$	None	$1/DBH^k$	8344	0.897	37.8	−10.6	28.0
$AGB = a \times (DBH^2H)^b$	Ecoregion[a]	$1/(DBH^2H)^k$	8311	0.903	37.6	−10.4	27.4
	WD class[a]		8122	0.935	30.8	−7.4	22.3
	Family[a]		8245	0.923	34.9	−9.0	25.4

[a] Selected model.

examined. Better fit and validation statistics were achieved with the model form $AGB = a \times (DBH^2H)^b$ (Table 6). Therefore, mixed effects models were fit with DBH^2H as the covariate. Fit and validation statistics for these models are shown in Table 6.

The random effect of *WD* resulted in the greatest improvement in fit and validation statistics between the mixed effects models. Plant family also resulted in substantial improvements in all fit statistics over the fixed effect model. While including ecoregion did not result in the same magnitude of reductions in RMSPE, percent bias, and MAPE as the random effect of plant family, it improved AIC in comparison to the fixed effect model.

All of the mixed effects models examined resulted in substantial changes in parameter estimates when compared to the fixed effect model. The parameter estimates and standard errors of the selected fixed effect and mixed effects models with random effects of ecoregion, *WD* class, and plant family are provided in Table 7. The fitted values vs. the entire dataset for developing equations and the predicted values vs. a validation dataset are shown in Fig. 4. Fig. 4 indicates that there are sizable differences in *AGB* estimates when *WD* class and family are included as random effects. Marginal differences were observed when ecoregion was included as a random effect.

3.3. Model AGB = f(DBH, WD)

The power models incorporating *DBH* and *WD* as covariates tested in this study were of the form $AGB = a \times DBH^bWD$ and $AGB = a \times DBH^bWD^c$. These models had very similar values for AIC and comparable fit statistics (Table 8). Therefore, the model $AGB = a \times DBH^b \times WD$ was selected as it had fewer parameters. As shown in Table 8, the random effect of ecoregion increased the accuracy of the *AGB* estimates over the fixed effects model, lowering AIC, RMSPE, and MAPE while increasing the adjusted R^2. Including plant family as a random effect also lowered AIC compared to the fixed effects model. However once models were fit using the entire data set, the mixed effects model with ecoregion as a random effect resulted in more substantial changes to parameter estimates over the fixed effects model than plant family (Table 9). Fig. 5 shows fitted and predicted curves of the mixed model with random effect of ecoregion overlaid on plots of the entire dataset and a validation dataset, respectively.

3.4. Model AGB = f(DBH, H, WD)

For predicting *AGB* with *DBH*, *H*, and *WD* the fixed effects model forms $AGB = a \times (DBH^2HWD)^b$ and $AGB = a \times DBH^bH^cWD^d$ were examined. Although the model $AGB = a \times DBH^bH^cWD^d$ preformed slightly better with respect to fit statistics (AIC and Adj. R^2) (Table 10), the DBH^2HWD model preformed comparably well and has fewer parameters. Therefore, mixed effects models were fit based on the $AGB = a \times (DBH^2HWD)^b$ model form.

Including the random effect of ecoregion resulted in an increased adjusted R^2 and reduced AIC and MAPE compared to the fixed effect model of the same form (Table 10). While plant family highered AIC, it resulted in increases in RMSPE, percent bias, and MAPE, and had similar adjusted R^2 as the fixed effect model. However, both random effects resulted in substantial changes to parameter estimates when compared to the fixed effect model (Table 11). The changes of its parameters under the effect of ecoregion are demonstrated in Table 11 and Fig. 5.

Fig. 6 shows the weighted fitted values and maximum likelihood weighted residuals for from one to three covariates. Fig. 7 shows the percent bias distribution across the 200 realizations of validation datasets and *AGB* predicted values for one of those validation datasets.

4. Discussion

In EBLF tree height generally indicates site productivity (Vanclay, 1992), microsite influences the relationships between height and diameter, and consequently the *AGB* estimate; but this fact is generally ignored. Additionally, the *WD* variable has the potential to be representative of different species. Most pan tropic equations to estimate *AGB* such as Brown (1997), IPCC (2003) and Basuki et al. (2009) use only *DBH* as a covariate.

For fixed effects models, we found that the *DBH* only model had the lowest accuracy compared with fixed effects models where *H* or *WD* were also considered as covariates. Adding *H* or *WD* to the *DBH* based model decreased MAPE by 3.2% or 9.1%, respectively, and when both *H* and *WD* were added to the *DBH* based model, there was an 11% decrease in MAPE. However, we also found that the AIC of the fixed models was substantially reduced when *WD* covariate was included in the model instead of *H* (Table 12), indicating that *WD* may be more important than *H* for reducing uncertainty in *AGB* estimates.

Table 7
Final parameter estimates, standard errors, and sample size obtained using the entire dataset for fixed and mixed effects models of the form $AGB = a \times (DBH^2H)^b$.

Random effect	Class	Parameters estimates		Standard error		Number of sample trees
		a	b	a	b	
None	–	263.9977	0.93645	2.778249	0.005567	968
Ecoregion	Central Highlands	304.1668	0.95102	1.583351	0.005603	222
	North Central Coastal	253.2449	0.95102	1.337745	0.005603	311
	Northeast	256.7133	0.95102	1.608920	0.005603	215
	South Central Coastal	272.0797	0.95102	2.249351	0.005603	110
	Southeast	236.5860	0.95102	2.249351	0.005603	110
Wood density	⩽0.40 g/cm^3	198.2493	0.93333	3.393656	0.004659	151
	0.41–0.60 g/cm^3	247.2759	0.93333	2.867241	0.004659	502
	>0.60 g/cm^3	320.8111	0.93333	3.448459	0.004659	315
Plant family	Dipterocarpaceae	313.3334	0.93293	4.497709	0.005167	85
	Euphorbiaceae	199.6983	0.93293	5.309283	0.005167	61
	Fagaceae	315.0759	0.93293	4.497709	0.005167	85
	Lauraceae	249.1764	0.93293	4.665383	0.005167	79
	Leguminosae	259.1900	0.93293	4.853325	0.005167	73
	Meliaceae	265.4258	0.93293	7.570772	0.005167	30
	Myrtaceae	321.5197	0.93293	5.492415	0.005167	57
	Ulmaceae	221.1848	0.93293	7.330369	0.005167	32
	Others	252.2186	0.93293	1.920914	0.005167	466

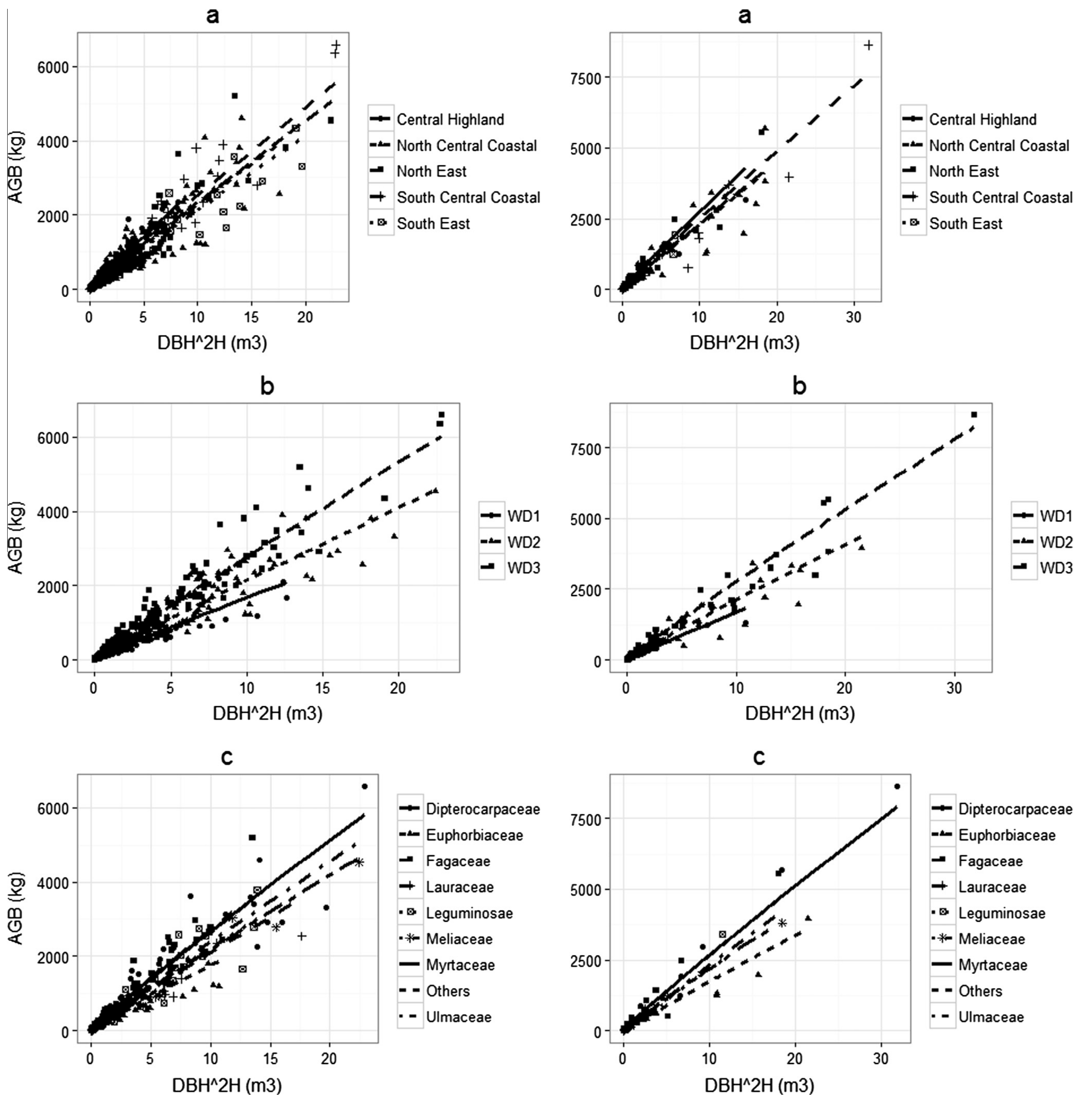

Fig. 4. Model $AGB = a \times (DBH^2H)^b$: (a) with random effect of ecoregion, (b) with random effect of *WD* class; (c) with random effect of main family. Left column plots are of fitted values vs. the entire dataset for developing equations and the right column plots are of predicted values vs. one of the validation datasets.

Table 8
Comparison and validation of different $AGB = f(DBH, WD)$ models with and without random effects.

Model form	Random effect	Weight variable	AIC	Adj. R^2	RMSPE	Percent bias	MAPE
$AGB = a \times DBH^b \times WD$	None[a]	$1/DBH^k$	8122	0.923	30.0	−4.5	21.4
$AGB = a \times DBH^b \times WD^c$	None		8094	0.926	31.3	−7.2	22.3
$AGB = a \times DBH^b \times WD$	Ecoregion[a]		8087	0.927	29.9	−4.8	21.0
	Family		8106	0.922	30.3	−4.6	21.5

[a] Selected model.

Table 9
Final parameter estimates, standard errors, and sample size obtained using the entire dataset for fixed and mixed effects models of the form $AGB = a \times DBH^b \times WD$.

Random effect	Class	Parameters estimates		Standard error		Number of sample trees
		a	b	a	b	
None	–	0.248329	2.386024	0.008997	0.011856	968
Ecoregion	Central Highlands	0.229594	2.461256	0.008331	0.001722	222
	North Central Coastal	0.229594	2.401649	0.008331	0.001455	311
	Northeast	0.229594	2.400294	0.008331	0.001750	215
	South Central Coastal	0.229594	2.409581	0.008331	0.002446	110
	Southeast	0.229594	2.391410	0.008331	0.002446	110
Plant family	Dipterocarpaceae	0.248326	2.386030	0.008997	0.011856	85
	Euphorbiaceae	0.248326	2.386030	0.008997	0.011856	61
	Fagaceae	0.248326	2.386030	0.008997	0.011856	85
	Lauraceae	0.248326	2.386030	0.008997	0.011856	79
	Leguminosae	0.248326	2.386030	0.008997	0.011856	73
	Meliaceae	0.248326	2.386030	0.008997	0.011856	30
	Myrtaceae	0.248326	2.386030	0.008997	0.011856	57
	Ulmaceae	0.248326	2.386030	0.008997	0.011856	32
	Others	0.248326	2.386030	0.008997	0.011856	466

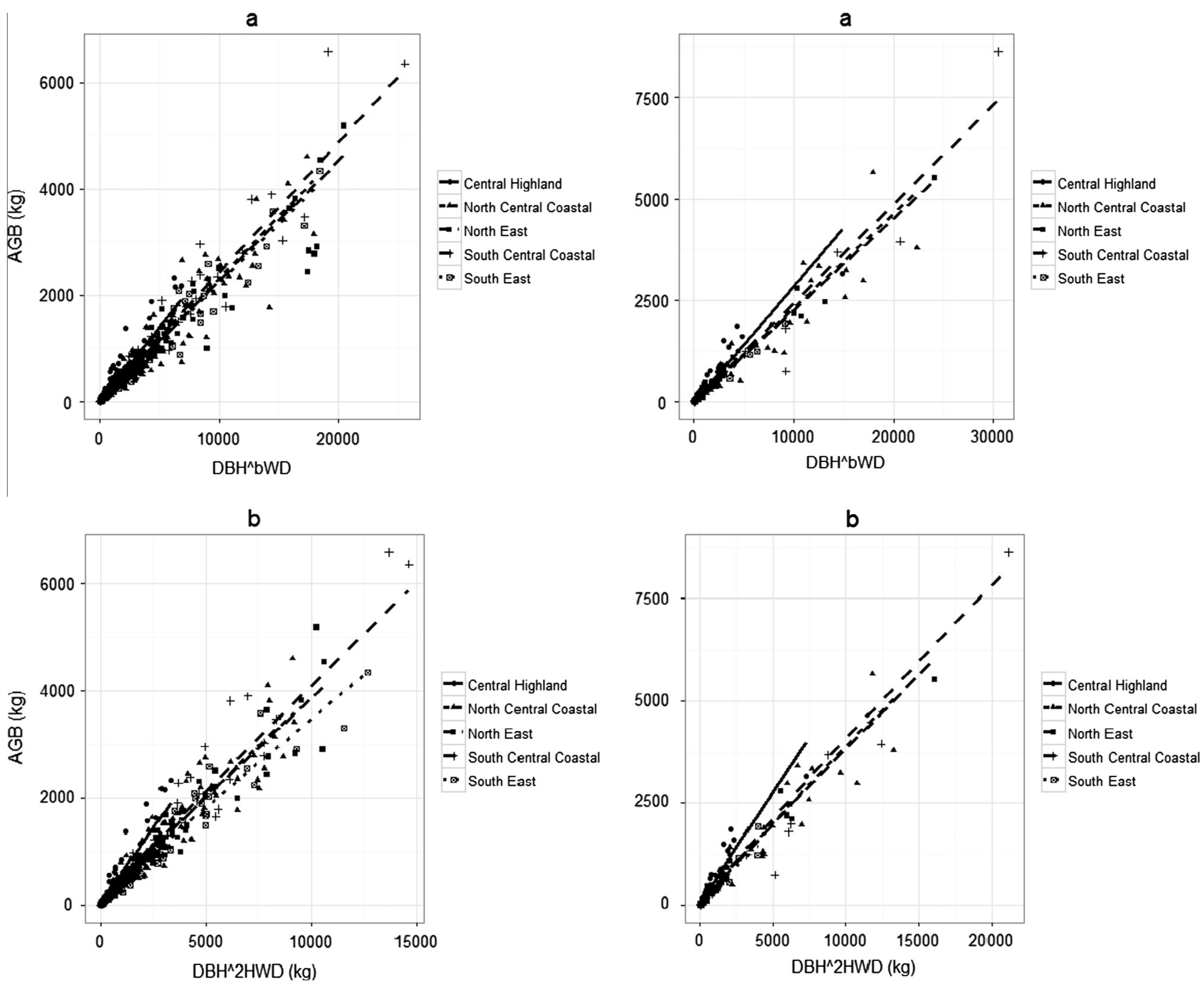

Fig. 5. Models with random effect of ecoregion, (a) Model $AGB = a \times DBH^b \times WD$ and (b) Model $AGB = a \times (DBH^2HWD)^b$. Left column plots are of fitted values vs. the entire dataset for developing equations and right column plots are of predicted values vs. one of the validation datasets.

In the absence of random effects, increasing the number of covariates from one (*DBH*) to three (*DBH*, *H* and *WD*) reduced the AIC and MAPE of the estimates (Table 12). As a result of this and ecological knowledge of EBLF, the best option for estimating *AGB* was to use three covariates, *DBH*, *H*, and *WD* with the $AGB = a \times (DBH^2HWD)^b$ model form. However, we also need to recognize as a practical matter that the costs and errors of measurement may increase if more variables are used. Therefore,

Table 10
Comparison and validation of different $AGB = f(DBH, H, WD)$ models with and without random effects.

Model form	Random effect	Weight variable	AIC	Adj. R^2	RMSPE	Percent bias	MAPE
$AGB = a \times (DBH^2HWD)^b$	None[a]	$1/DBH^k$	8046	0.935	26.7	−2.1	19.6
$AGB = a \times DBH^b \times H^c \times WD^d$	None	$1/DBH^k$	7984	0.937	27.5	−6.1	20.0
$AGB = a \times (DBH^2HWD)^b$	Ecoregion[a]	$1/(DBH^2HWD)^k$	7987	0.943	28.0	−5.9	19.5
	Family		8177	0.934	28.8	−7.5	21.3

[a] Selected model.

Table 11
Final parameter estimates, standard errors, and sample size obtained using the entire dataset for fixed and mixed effects models of the form $AGB = a \times (DBH^2HWD)^b$.

Random effect	Class	Parameters estimates		Standard error		Number of sample trees
		a	b	a	b	
None	–	0.806438	0.920321	0.024255	0.004930	968
Ecoregion	Central Highlands	0.798788	0.965553	0.003522	0.000806	222
	North Central Coastal	0.680529	0.938471	0.002975	0.000681	311
	Northeast	0.680064	0.938364	0.003578	0.000819	215
	South Central Coastal	0.685211	0.939543	0.005003	0.001145	110
	Southeast	0.647261	0.930852	0.005003	0.001145	110
Plant family	Dipterocarpaceae	0.809935	0.919647	0.007371	0.000085	85
	Euphorbiaceae	0.775496	0.920044	0.008701	0.000100	61
	Fagaceae	0.964170	0.917868	0.007371	0.000085	85
	Lauraceae	0.814778	0.919591	0.007646	0.000088	79
	Leguminosae	0.786264	0.919920	0.007954	0.000092	73
	Meliaceae	0.845066	0.919242	0.012407	0.000143	30
	Myrtaceae	0.904027	0.918562	0.009001	0.000103	57
	Ulmaceae	0.776853	0.920028	0.012013	0.000139	32
	Others	0.777449	0.920022	0.003148	0.000036	466

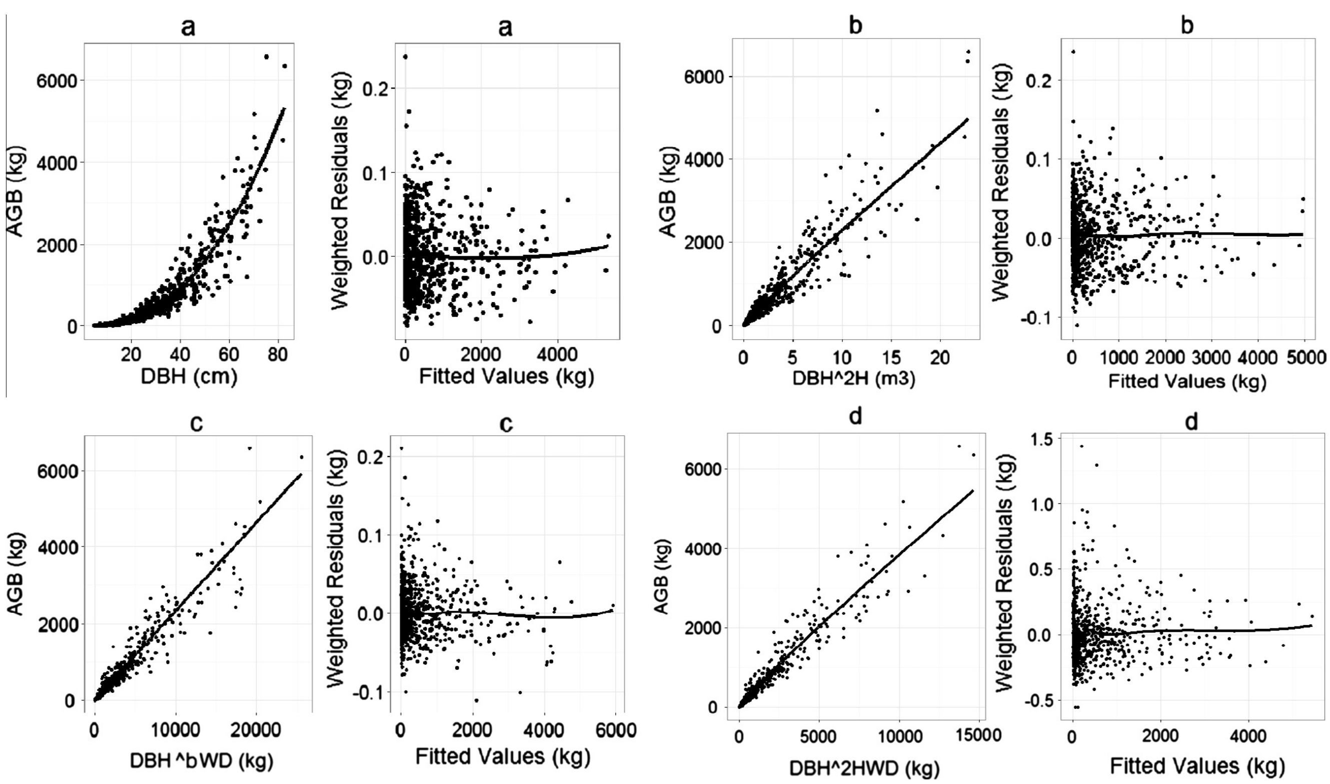

Fig. 6. Plots of AGB models without random effects: Weighted Fitted and Maximum Likelihood weighted residuals. (a) For model of $AGB = a \times DBH^b$, (b) for model of $AGB = a \times (DBH^2H)^b$, (c) for model $AGB = a \times DBH^b \times WD$, and (d) for model of $AGB = a \times (DBH^2HWD)^b$.

the context of using equations with different sets of predictors is very important.

For mixed effects models where *WD* was not included as a covariate (e.g. $AGB = f(DBH)$ or $AGB = f(DBH, H)$), the best results were obtained with the random effect of *WD* classes. When *WD* variable was included with other fixed effect covariates, such as $AGB = a \times DBH^b \times WD$ or $AGB = a \times (DBH^2HWD)^b$, then ecoregion as a random effect helped reduce uncertainty of estimates.

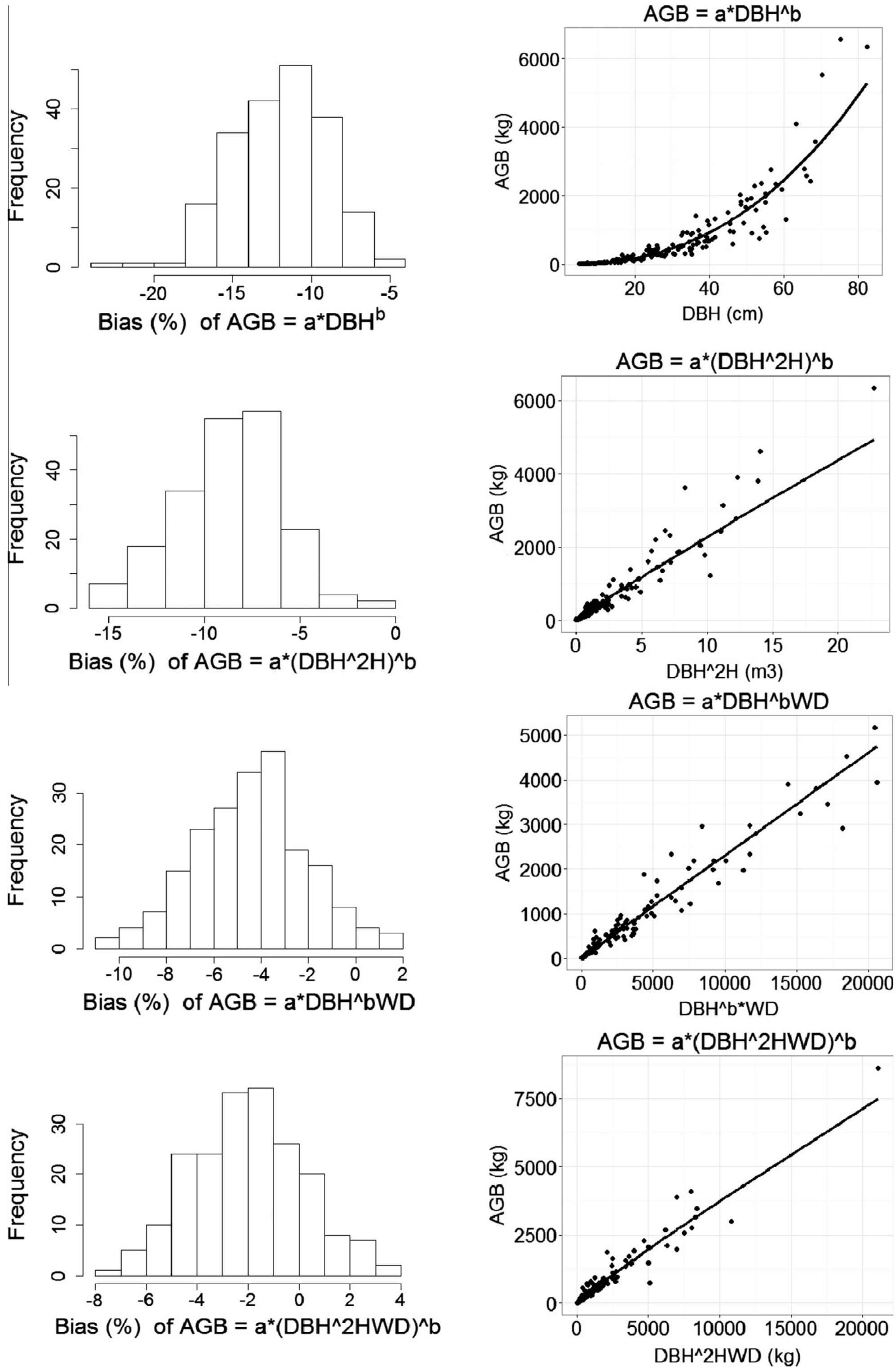

Fig. 7. Percent bias distribution from over 200 realizations of the validation dataset (left) and predicted AGB values from selected equations without random effects vs. one of the validation dataset realizations (right).

The highest preforming model in this study used a combination of the three variables (DBH^2HWD) and the random effect of ecoregion. This model had a low AIC and with 19.5 MAPE. This result is consistent with findings in a study by Ketterings et al. (2001) from Sumatra where site-specific power biomass models were found to outperform generic power models without a site specification. Therefore ecoregion should be recognized as an important factor in estimating *AGB* and improving the accuracy of the biomass estimate for pan tropic forest that have varied microsites conditions.

While most *AGB* equations for the pan tropic region only use dendrometric variables (*DBH*, *H*, *WD*) as covariates, this study shows that *AGB* is also influenced by ecoregion and taxonomic factors (plant family). These factors when included as random effects increased the accuracy of the biomass estimates for EBLF of Viet

Table 12
Comparison and validation of the best models with and without random effects for each combination of input variables.

Model form	Random effect	Weight variable	AIC	MAPE
$AGB = a \times DBH^b$	None	$1/DBH^k$	8425	30.6
$AGB = a \times (DBH^2H)^b$	None	$1/DBH^k$	8342	27.4
$AGB = a \times DBH^b \times WD$	None	$1/DBH^k$	8122	21.5
$AGB = a \times (DBH^2HWD)^b$	None	$1/DBH^k$	8046	19.6
$AGB = a \times DBH^b$	WD class	$1/DBH^k$	8292	23.0
$AGB = a \times (DBH^2H)^b$	Ecoregion	$1/(DBH^2H)^k$	8311	27.4
$AGB = a \times (DBH^2H)^b$	Family	$1/(DBH^2H)^k$	8245	25.4
$AGB = a \times (DBH^2H)^b$	WD class	$1/(DBH^2H)^k$	8122	22.3
$AGB = a \times DBH^b \times WD$	Ecoregion	$1/DBH^k$	8087	21.0
$AGB = a \times (DBH^2HWD)^b$	Ecoregion	$1/(DBH^2HWD)^k$	7987	19.5

Nam over fixed effects models. The mixed effects modeling approach used in this study helped determine the influence of factors such ecology, environment, and plant on biomass estimates.

5. Conclusions

Overall, this study found $AGB = a \times (DBH^2HWD)^b$ with ecoregion as a random effect to be the best model for estimating *AGB* of EBLF in Viet Nam. The development and testing of the tree aboveground biomass models for EBLF yielded the following main conclusions.

5.1. Fixed effects models

The best modeling option for fixed effects models incorporated a covariate that was a combination of *DBH*, *H*, and *WD* in the form of the equation $AGB = a \times (DBH^2HWD)^b$. If only *DBH* and either *WD* or *H* measurements are available, including *WD* proved to be more important for increasing accuracy and the proportion of variation explained by the model than including *H* for *AGB*.

5.2. Mixed effects models

For models without *WD* as a covariate, including *WD* classes as a random effect improved model performance and accuracy, and therefore the reliability of estimating *AGB*. This highlights the importance of *WD* in modeling *AGB* of EBLF in Viet Nam.

Including ecoregion as a random effect improved estimates of EBLF for $AGB = f(DBH, WD)$ and $AGB = f(DBH, WD, H)$ models. However, ecoregion as a random effect did not have a substantial impact on *DBH* and DBH^2H models. Therefore, while ecoregion may increase the reliability of *AGB* estimates, only substantial benefit is seen when *WD* is included as a covariate.

Plant family helped to explain variability in *AGB* estimates for *DBH* and DBH^2H models by increasing Adjusted R^2 and reducing AIC, RMSPE, percent bias, and MAPE. However fit and validation statistics for the best fixed effects model, $AGB = f(DBH, H, WD)$, and the $AGB = f(DBH, WD)$ model were not substantially improved by adding plant family as a random effect. This might be due to plant family acting as a surrogate for *WD*.

We foresee future work in several directions. Examination of below ground biomass to account for total carbon stored in evergreen broadleaf forests of Viet Nam. Estimating below ground biomass of trees will improve the inference of this study and account a major component of carbon storage of these forests. Because stand age and composition affect biomass allocation, we suggest developing equations that account for component biomass using new sets of equations or biomass conversion and expansion methods to improve total above- and belowground biomass and its components.

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