XV WORLD FORESTRY CONGRESS
Building a Green, Healthy and Resilient Future with Forests
2–6 May 2022 | Coex, Seoul, Republic of Korea

Allometric equation for estimating tree above ground biomass modified by ecological environmental factors in tropical dipterocarp forests

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Abstract

Tropical Dipterocarp Forest (DF) plays an important role in mitigating climate change thanks to its carbon sequestration capacity. In order to estimate the CO_2 absorption capacity of DF as a basis for the development of forest ecological services, a system of biomass equations is needed; while very few models for estimating biomass in DF have been published and have not yet reflected the impact of ecological environmental factors. The purpose of the study was to validate and select the best model for estimating tree above ground biomass (*AGB*, kg) in DF under the influence of ecological environmental factors, thereby improving the reliability. Twenty-eight 0.25 ha plots in the Central Highlands and one 1 ha plot in the Southeast ecoregion in Viet Nam were measured. A total of 329 trees were destructively sampled to obtain a dataset of AGB; Methods for developing equations were weighted nonlinear fixed/ mixed models with/without random effects fit by Maximum Likelihood; Using K-fold cross validation with K = 10, we compared and selected the best model with and without ecological environmental factors. As a result, separate ecological environmental factors did not affect *AGB*, while the combination of the factors influences the *AGB* model through the form: $AGB = AVERAGE \times MODIFIER$, $AGB = a \times D^b \times WD^d \times \exp(e_2 \times (P - 1502) + e_3 \times (BA - 12.62))$ that was significantly more reliable than a model without these factors involved; where D (cm), WD (g / cm^3), P (mm year^{-1}) and BA (m^2 ha^{-1}) are the diameter at breast height, wood density, averaged annual rainfall and total basal area of forest stand, respectively.

Keywords: above ground biomass, dipterocarp forest, ecological factor

Introduction, scope and main objectives

The Dipterocarp Forest (DF) is a unique forest type in Viet Nam, Southeast Asia, and South Asia, dominated by species of the Dipterocarpaceae family that are distributed in the extreme environmental conditions of sites (e.g., forest fires and drought in the dry season, and waterlogging in the rainy season) (Huy et al., 2018, 2019a). DF plays an important role in climate change mitigation due to the carbon sequestration capacity of species in the Dipterocarpaceae family. To estimate the CO_2 absorption of the dipterocarp forest as a basis for the development of forest ecological services, it is necessary to develop a modeling system for estimating tree above ground biomass (*AGB*).

Currently, for the model that estimate the biomass and carbon of dipterocarp forests in the world, there are only a few publications, Huy et al. (2016c) and Kralicek et al. (2017) in Viet Nam and Basuki et al. (2009) for Indonesia. Kralicek et al. (2017) is a rare publication referring to an estimation of the tree belowground biomass (*BGB*) model of the dipterocarp forest, because of the difficulty and high cost of collecting biomass data for DF tree root systems.

The methods of developing tree biomass models include the selection of predictors for the model, the model form, the method for developing equations, and the validation of errors. There are three common predictors of the tree *AGB* models which are diameter at breast height (*D*), tree height (*H*), and wood density (*WD*) for estimating tree biomass of mixed species and in other ecological regions; the power function is not the most accurate compared to other complex models, but seems to be suitable in many cases (Picard et al., 2015); and weighted non-linear model fit by Maximum Likelihood has higher reliability than log-transformed model; and cross-validation objectively reflect the errors of the biomass models (Chave et al., 2005, 2014; Huy et al., 2016a,b,c, 2019a,b).

On the other hand, the biomass of forest trees is not only related to the forest tree variables but is also influenced by the ecological environmental factors when the model is established in different sites, ecological regions, and forest states.

Therefore, this study was to develop and cross-validate the DF's tree biomass estimation modeling system in which the biomass model was adjusted according to ecological environmental factors to improve reliability.

Methodology

1. Study sites

The study sites were in the north latitude: 11^{0}20'N - 13^{0}30'N and east longitude: 107^{0}35'E - 108^{0}45'E in two ecoregions, the Central Highlands (CH) and the Southeast (SE) in Viet Nam (Fig. 1)

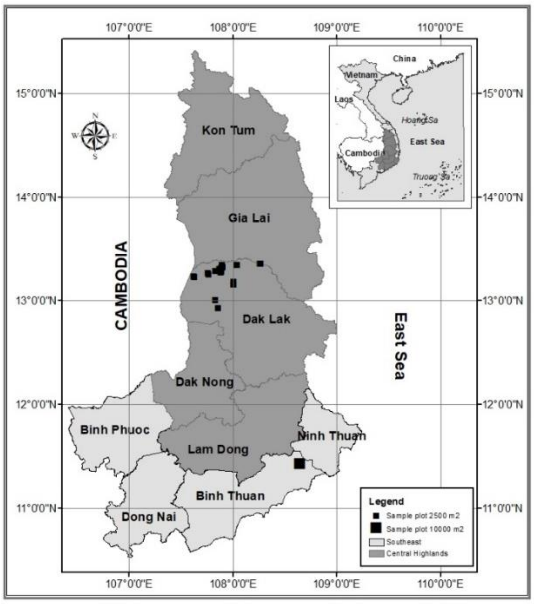

Fig. 1. Map of the distribution of sample plots in tropical dipterocarp forests in the Central Highlands and Southeast ecoregions of Viet Nam (Huy et al., 2019a).

The average annual rainfall in CH is 1,600 mm and in SE is 1,003 mm, with the average annual temperature of 25.3 ^{0}C - 25.5 °C, the dry season lasts 3 - 4 months. The altitude in the study areas ranges from 171 to 417 m, the topography of the study area is relatively flat, and the soil is mainly of volcanic origin (Source: From the study; Hijmans et al., 2005; Fischer et al., 2008; Huy et al., 2018, 2019a).

2. Measurements

Twenty-eight of the 0.25 ha sample plots in the CH ecoregion, the main distribution area of the DF in Viet Nam, and one 1 ha sample plot in the SE ecoregion were measured (Fig. 1). In the sample plots, the names of forest tree species were identified and measured diameter at breast height (D, cm) with D ≥ 5 cm and height of trees (H, m). The studied DF stands have a density (N, tree ha^{-1}) from 228 – 1,291 trees ha^{-1} (with D ≥ 5 cm), the stand basal area (BA, m^2 ha^{-1}) ranges from 3.8 to 23.4 m^2 ha^{-1} (Table 1).

Table 1. Statistical data on ecological and environmental factors in the dipterocarp forests studied

Ecological and environmental factors	Min	Mean	Max	Sd
Altitude (m)	171	246	417	64,6
Slope (degree)	0	2.0	8.0	2.2
Annual rainfall averaged (P, mm $year^1$)	1003	1502	1600	221.5
Annual temperature averaged (T, ^{0}C)	25.3	25.4	25.5	0.07
Soil type	Igneous Rocks			
Basal area (BA, m^2 ha^{-1} with D ≥ 5 cm)	3.78	12.62	23.41	5.61
Density (N, tree ha^{-1} with D ≥ 5 cm)	228	534	1292	256.4

Source: From the study; Hijmans et al., 2005; Fischer et al., 2008; Huy et al., 2018, 2019a

In each sample plot and the study area ecological environmental data such as altitude (m), slope (degree), annual rainfall averaged (P, mm $year^{-1}$), annual temperature averaged (T, °C), soil type were collected (Table 1). In which, factors with the variation were studied for their random effects on tree biomass models such as Ecoregions, Altitude, P, BA, and N.

The biomass model in this study aims to achieve reliability as required by the IPCC (2003, 2006), so the biomass dataset was collected directly by destructive sampling. The DF is an uneven age mixed species forest; therefore, the selection of the sample trees was proportional to the diameter distribution of the stand and proportional to the dominant species (Fig. 2). A total of 329 sample trees were cut to collect fresh biomass data of tree components and sampled to determine the dry and fresh biomass ratio of each tree component (Huy et al., 2019a).

Before cutting the sample trees, measure D and H and determine the species name. Tree height was measured again after the sample tree was cut. The weights of fresh biomass of plant components such as leaves, branches, stems, and bark were weighed and recorded. Samples of wood parts and sample bark were 500 g and 300 g respectively and were sampled at 5 segments of the trunk. The sample of branches was 500 g and 3 samples were collected at three positions per branch (large, medium, and small). The leaf sample is 300 g consisting of two samples of old and young leaves. Samples of the four components of plant were sent to the laboratory to calculate the fresh to fry weight ratio, and the wood density (WD, g/cm^3).

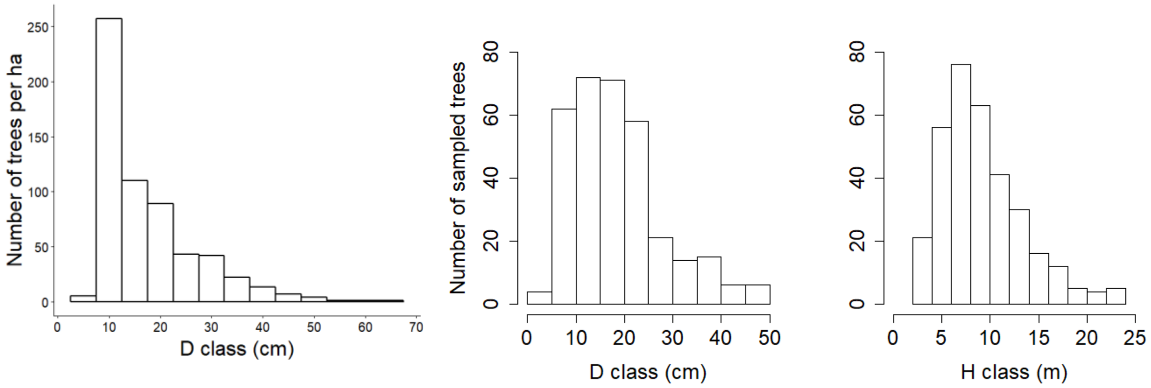

Fig. 2. Distribution of diameter in all sample plots per ha (left). Distribution of diameter (middle) and height (H, m) (right) of destructively sampled trees (Huy et al., 2019a).

While in the laboratory, the fresh volume of the wood samples was determined by an in vitro water displacement method. All samples were chopped and dried at 105 °C until constant weight. The WD (g/cm^3) of the sample was taken as the ratio of the dry mass to the fresh volume of each sample. WD for each sample tree was averaged from five segments (Huy et al., 2016a). The dry biomass of each plant component was calculated by its fresh weight multiplied by the fresh to dry ratio. The aboveground biomass (*AGB*, kg) of each sample tree is the sum of stem biomass (*Bst*), branches biomass (*Bbr*), leaves biomass (*Bl*), and bark biomass (*Bba*) (Table 2) (Huy et al., 2016a, 2019a).

Table 2. Summary statistics for predictor and response variables of destructively sampled trees (n = 329)

Variable	Min	Mean	Max	Sd
D (cm)	3.4	18.1	48.8	9.751
H (m)	2.5	9.2	23.5	4.238
WD (g/cm^3)	0.379	0.662	0.953	0.096
Bst (kg)	0.5	95.1	885.3	148.704
Bbr (kg)	0.2	49.8	607.5	86.939
Ble (kg)	0.1	5.3	42.4	6.238
Bba (kg)	0.1	27.7	311.0	45.638
AGB (kg)	1.3	177.9	1719.8	277.770

Source: Huy et al., 2019a

3. Model fitting

Selection of predictors for the tree AGB model for the dipterocarp forests:

This study according to Huy et al. (2016c, 2019a) uses three predictors *D, H,* and *WD* for the *AGB* model for estimating mixed-species biomass.

Select the form of the AGB equation:

Based on publications (Brown, 1997; Basuki et al., 2009; Chave et al., 2005, 2014; Picard et al., 2015; Kralicek et al., 2017; Huy et al., 2016 a,b,c, 2019a), this study applied the Power form to fit tree biomass modeling system with three predictors such as *D, H,* and *WD*.

Weighted non-linear mixed effects model fit by Maximum Likelihood:

There was heteroscedasticity in the residuals of the *AGB* model; therefore, weighted regression was used in this study (Huy et al., 2019 a,b, 2020; Davidian and Giltinan, 1995; Picard et al., 2012). Using the Furnival index (Furnival, 1961; Jayaraman, 1999), we compared the performance of log-linear and non-linear power models and because of that comparison, the nonlinear model was selected. This is consistent with Huy et al. (2016c, 2020).

Weighted non-linear mixed effects models were fit by maximum likelihood and the random effects were incorporated to account for the variability due to ecological environmental factors (Xu et al, 2014; Bates, 2010; Pinheiro et al., 2014; Timilsina and Staudhammer, 2013; Huy et al., 2020). The mixed effects model was fit by using nlme package in statistical software R (R Core Team, 2019) and had the following general form (Timilsina and Staudhammer, 2013; Huy et al., 2016 a,b,c; Kralicek et al., 2017; Huy et al., 2020):

$$Y_{ij} = (a + \alpha_i) \times X_{ij}{}^{(b+\beta_i)} + \varepsilon_{ij} \quad (1)$$

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

where $Y_{i,j}$ is a vector of tree ith *ABG* (kg) measurements from the jth class of a factor; $X_{i,j}$ are the predictors (D, cm; H, m and WD, g/cm^3) of the tree ith in jth of the class of a factor; a and b are vectors of fixed-effects parameters; α_i and β_i are vectors of random effects parameters associated with the jth class of a factor; ε_{ij} is the random error associated with the ith sample and jth class of a factor.

The variance function was as follows (Huy et al., 2016 a,b,c; 2020):

$$\mathrm{Var}(\varepsilon_i) = \widehat{\sigma^2}(\nu_i)^{2\delta} \quad (3)$$

where $\widehat{\sigma^2}$ is the estimated error sum of squares; ν_i is the weighting variable (*D*) associated with the ith sampled tree, and δ is the variance function coefficient to be estimated.

The following factors for random effects were examined: (i) ecoregions in two sites in CH and SE; (ii) altitude (≤ 200 m, 201 m to 350 m, and > 350 m); iii) annual rainfall averaged P (1003 and 1600 mm year^1); iv) stand basal area BA (≤ 10, 11 – 20, and > 20 m^2 ha^{-1}), stand density N (≤ 300, 301 – 700, and > 700 trees ha^{-1}).

Development of a fixed effect model with the combination of factors:

The mixed effects *AGB* model with random effects of ecological environmental factors sets up a single model with each factor. Meanwhile, these factors interact and have synergistic effects on *AGB* (Huy et al., 2020). Therefore, a fixed-effects model that incorporates a combination of ecological environmental factors was examined to select the best model.

In this case, the form of the tree *AGB* model consists of two components, an average *AGB* model and a modifier (Lessard et al. 2001; Huy et al., 2020) as follows:

$$AGB = AVERAGE \times MODIFIER \quad (4)$$

where AVERAGE is the selected average fixed model: AVERAGE = $Y_i = a \times X_i{}^b + \varepsilon_i$

and MODIFIER = $\prod_{j=1}^{n} \exp\left[\mathrm{e}_j \text{ (factor j − average value of factor j)}\right]$

where Y_i is a vector of *AGB* measurements of the i[th] sample tree, X_i is the predictor(s) (*D, H, WD*) associated with the i[th] tree sampled, a and b are vectors of the fixed parameter of the selected average *AGB* model, n is the number of factors, e_j is a vector of the parameter of factor j and the average value of factor j presented in Table 1, and ε_i is the random error of the model.

The modifier is an exponential equation that involves ecological environmental factors as additional covariates. The modifier adjusts the *AGB* estimates based on the combined effects of these factors. In this study, factors consisted of Altitude, P, BA, and N. Average values of the factors were incorporated into the modifier, so that the higher the observed variable's value than the average value, the greater the effect on the diameter prediction.

To develop the equation (4), weighted non-linear fixed-effects models were fit by Maximum Likelihood method (Davidian and Giltinan, 1995; Lessard et al. 2001; Bates, 2010; Pinheiro et al., 2014; Huy et al., 2020) in nlme package in R (R Core Team, 2019).

4. Cross validation

K-fold with K=10 cross validation (Kohavi, 1995; Picard et al., 2012; Moore, 2017; Huy et al., 2019a) was performed to cross-validate the developed models. The dataset was randomly split into K equal-sized subsamples, in which K - 1 subsamples were used to develop models and the remaining K subsample were used to assess model performance. The cross-validation process was repeated 10 times and the statistics for the comparison and validation of the models were averaged over 10 realizations.

The Akaike information criterion (AIC) (Akaike, 1973) was used as a key statistic to compare and select the optimal models. The model that had the lowest AIC value was selected as the best model. Along with AIC, adj. R^2, the statistical significance of the parameters (p-value < 0.05), diagnostic plots of the residual trend were also used to assess the performance of the model. For cross-validation of the developed models, errors such as bias (%), root mean square error (RMSE, %), and mean absolute percent error (MAPE, %) (Swanson et al., 2011; Huy et al., 2016a,b,c; Huy 2019a) were calculated. All statistics were calculated using the cross-validation procedure. Smaller values for indicators are preferred.

$$Bias\ (\%) = \frac{1}{K}\sum_{k=1}^{K} \frac{100}{n}\sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i} \tag{5}$$

$$RMSE\ (\%) = \frac{1}{K}\sum_{k=1}^{K} 100 \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \tag{6}$$

$$MAPE\ (\%) = \frac{1}{K}\sum_{k=1}^{K} \frac{100}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \tag{7}$$

where K is the number of folds (10); n is the number of sampled trees for validation, and *yi*, $\hat{y}_i$ are observed, predicted *AGB* for the i[th] sampled tree in realization K, respectively.

The final parameter estimates for all the selected modeling systems were obtained by fitting the models with the entire dataset.

Results

1. Random effects of each ecological environment factor on the AGB model

This study examined the random effects of each ecological, environmental, and forest stand factor such as Ecoregion, Altitude, P, N, and BA on the selected DF tree *AGB* biomass estimation model for mixed species: $AGB = a \times D^b \times H^c \times WD^d$. The result is presented in Table 3.

Table 3. Weighted nonlinear mixed models with random effects of ecological environmental factors and K-fold cross validation for selected model: $AGB = a \times D^b \times H^c \times WD^d$ for mixed- species of the DF.

Random effects	Weight variable	AIC	$R^2_{adj.}$	RMSE %	Bias %	MAPE %
None	$1/D^\delta$	2664	0.910	-11.1	44.6	27.1
Ecoregion	$1/D^\delta$	2659	0.913	-11.1	44.3	27.4
Altitude classes (m)	$1/D^\delta$	2663	0.910	-11.0	46.0	27.1
Annual rainfall averaged classes (P, mm $year^{-1}$)	$1/D^\delta$	2663	0.910	-11.1	45.5	27.2
Basal area classes (BA, $m^2\ ha^{-1}$)	$1/D^\delta$	2645	0.910	-11.0	45.7	27.3
Density classes (N, tree ha^{-1})	$1/D^\delta$	2646	0.910	-11.1	43.7	27.1

Note: In K-fold cross validation, the dataset is randomly split into equal-sized subsamples of K (K= 10 folds), K - 1 subsamples used for developing models, calculation of AIC, Adj. R^2; and K remaining subsample used for validation, calculation of Bias, RMSE, MAPE; finally, all those statistics averaged over 10 realizations. δ: the variance function coefficient.

Table 3 shows that through cross-validation of K-Fold with each ecological environmental factor separately, it did not show its influence on the tree *AGB* biomass model of mixed species of the DF. Models include each factor with statistical values AIC, $R^2_{adj.}$ and errors such as Bias, MAPE, and RMSE had no significant differences compared to the model without considering the effects of these factors.

2. Effects of the combination of ecological environment and forest stand factors on tree AGB biomass model of the DF

Develop and cross-evaluate the combined effects of four factors of ecology environmental and forest stand including Altitude, P, BA, and N on the average *AGB* estimation model as the following:

$$AGB = AVERAGE \times MODIFIER = a \times D^b \times H^c \times WD^d \times \exp\left(e_1 \times (Altitude - 246) + e_2 \times (P - 1502) + e_3 \times (BA - 12.62) + e_4 \times (N - 534)\right) \quad (8)$$

In which the MODIFIER function was used to adjust the predicted *AGB* biomass when the ecological, environmental and forest stand changes compared to its average value. The results show in Table 4.

The result of selecting the model (Table 4) to estimate *AGB* of dipterocarp forest trees with combined factors effects is presented as the following model form:

$$AGB = a \times D^b \times WD^d \times exp(e_2 \times (P - 1502) + e_3 \times (BA - 12.62)) \quad (9)$$

Table 4. Cross validation using K fold for comparison and selection of equation form based on fixed effect model for *AGB without/*with ecological environmental and forest stand variables included

Id	Model form	Weight variable	AIC	$R^2_{adj.}$	Bias (%)	RMSE (%)	MAPE (%)
1	$AGB = a \times D^b \times H^c \times WD^d$	$1/D^\delta$	2664	0.910	-11.1	44.6	27.1
2	$AGB = a \times D^b \times H^{c^*} \times WD^d \times exp(e_1 \times (Altitude - 246) + e_2 \times (P - 1502) + e_3 \times (BA - 12.62) + e_4^* \times (N - 534))$	$1/D^\delta$	2681	0.930	-9.5	41.7	25.0
3	$AGB = a \times D^b \times WD^d \times exp(e_1^* \times (Altitude - 246) + e_2 \times (P - 1502) + e_3 \times (BA - 12.62))$	$1/D^\delta$	2650	0.927	-10.0	41.2	25.5
4	$\mathbf{AGB = a \times D^b \times WD^d \times exp(e_2 \times (P - 1502) + e_3 \times (BA - 12.62))}$	$\mathbf{1/D^\delta}$	**2640**	**0.926**	**-9.9**	**41.5**	**25.3**

Note: Altitude in m, annual rainfall averaged (P, mm $year^{-1}$), basal area (BA, $m^2\ ha^{-1}$), and density (N, tree ha^{-1}). In K-fold cross validation, the dataset is randomly split into equal-sized subsamples of K (K= 10 folds), K - 1 subsamples used for developing models, calculation of AIC, Adj. R^2; and K remaining subsample used for validation, calculation of Bias, RMSE, MAPE; finally, all those statistics averaged over 10 realizations. *: Parameter with P-value > 0.05. δ: the variance function coefficient; Bold: A selected model based on K-fold cross validation statistics and diagnostic plots.

Model (9) with the combination of two factors P and BA in the *AGB* estimation model with two predictors D and WD has improved the reliability in that the AIC and error values are lower than of the model without the factors of ecology, forest stand (Table 4). The parameters of the model (9) were estimated using the entire dataset presented in Table 5

Table 5. The parameters of the *AGB* model which included two tree predictors D and WD and two factors of P and BA

Model form	Parameter	Parameter ± Approx. Std Error
$AGB = a \times D^b \times WD^d \times$	a	0.127751 ± 0.015243
$exp(e_2 \times (P - 1502)$	b	2.460833 ± 0.031600
$+ e_3 \times (BA - 12.62))$	d	0.978793 ± 0.122928
	e_2	-0.000645 ± 0.000095
	e_3	-0.008556 ± 0.003552

Note: P: annual rainfall averaged (mm $year^{-1}$), BA: basal area (m^2 ha^{-1})

The results in the graphs in Fig. 3 show that the model *AGB = AVERAGE × MODIFIER* has high reliability with the strong relationship between estimated and observed *AGB* values and especially the weighted residuals fluctuated ± 0.05 kg $tree^{-1}$ and spread evenly according to the estimated *AGB* by the selected model.

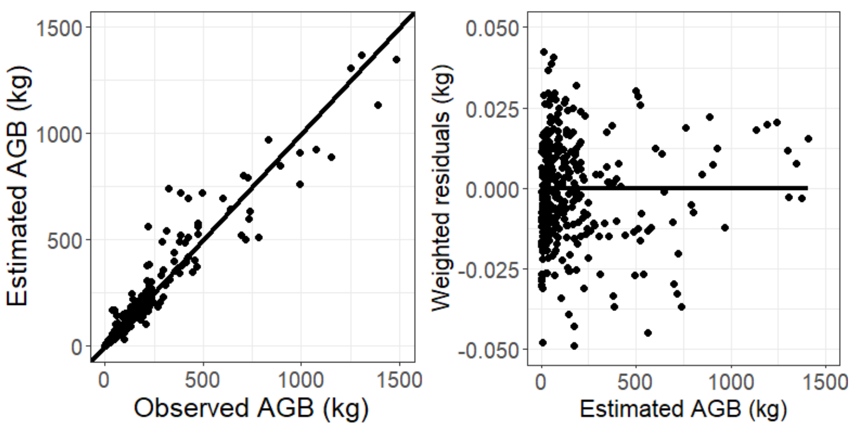

Fig. 3. Model *AGB = AVERAGE × MODIFIER* under the combined effects of ecological, environmental, and forest stand factors: Estimated vs. observed *AGB* (left); Weighted residuals vs. estimated *AGB* (right)

Discussion

Random effects are essential to account for the effects of the different sites on the tree biomass model when the site index has not been identified (Timilsina and Staudhammer, 2013); however, in this case, the random effects of a separate factor did not help improve the *AGB* estimates (Table 3). Therefore, it demands to review the synthesis effects of factors in the models to improve the reliability and reduce the estimation errors of dipterocarp forest tree biomass in different sites.

The results showed that the H predictor had no significance (P-value > 0.05) (Table 4) in the selected model. This can be explained that the variable H represents the change in site, and when some ecological factors reflect the site of the dipterocarp forest, such as rainfall, altitude included, the effect of H on the model *AGB* no longer makes sense.

When using the combination of ecological and forest stand factors in the fixed *AGB* model, the factors were related to each other (Huy et al., 2020) and simultaneously affect *AGB* estimates and help improve the reliability when the model is created at different sites of the dipterocarp forests.

From the parameters of the selected model (Table 5), it shows that the two factors *P* and *BA* had negative parameters (< 0), this means that the average annual rainfall P is higher than 1502 mm $year^{-1}$ or the basal area BA of the stand is greater than 12.62 m^2 ha^{-1}, thereby reducing the amount of tree biomass accumulation in the DF. In other words, tree biomass accumulation of Dipterocarp forest increases where the rainfall is less than 1502 mm $year^{-1}$ and the stand is not mature and the volume is not high, with BA < 12.62 m^2 ha^{-1}.

Conclusions

Considering the single ecological environment factor, it did not show its influence on the tree *AGB* biomass model of dipterocarp forests. With the model *AGB = AVERAGE × MODIFIER*, where averaged *AGB* model adjusted by a combination of ecological and environmental factors had improved significantly the reliability compared to the *AGB* estimation model without these factors.

The study selected the best model to estimate the DF's tree *AGB* including two tree predictors *D* and *WD* and two factors of forest environment ecology *P* and *BA* in the form: $AGB = a \times D^b \times WD^d \times exp(e_2 \times (P - 1502) + e_3 \times (BA - 12.62))$.

Acknowledgments

The authors are grateful to the FREM field team, Tay Nguyen University (TNU), and those who were involved in a tremendous effort to collect one of the biggest databases of tree biomass. A part of the dataset came from the UN-REDD Program for Viet Nam and others from the Ph.D. training program at TNU.

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