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Additive modeling systems to simultaneously predict aboveground biomass and carbon for *Litsea glutinosa* of agroforestry model in tropical highlands

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Abstract

Aim of study: To develop and cross-validate simultaneous modeling systems for estimating components and total tree aboveground biomass and carbon of *Litsea glutinosa* in an agroforestry model with cassava.

Area of study: In the Central Highlands of Vietnam, the agroforestry model widely planted on fallow land of ethnic minorities is a mixture of 65% *L. glutinosa* in combination with 35% cassava (*Manihot esculenta*).

Materials and methods: Twenty-two 300-m^2 circular sample plots were located, representing the range of tree age, plantation density, and a 6-7 year rotation cycle. In each sample plot, one selected tree with a diameter at breast height equal to the plot quadratic mean diameter was destructively sampled. The relationships among tree aboveground biomass and carbon (*AGB/AGC*) and their components with dendrometric variables diameter, height, age, and crown area were examined using factor analysis. To fit systems of equations for *AGB/AGC* and their components, we compared two methods: weighted nonlinear least-squares (WNLS) and weighted nonlinear seemingly unrelated regression (WNSUR).

Main results: The results of the leave-one-out cross-validation showed that the simultaneous WNSUR approach to modeling systems of four tree components, total biomass, and carbon provided better results than independent WNLS models.

Research highlights: The simultaneous WNSUR modeling system provided improved and reliable estimates of tree components, total biomass, and carbon for *L. glutinosa* in an agroforestry model with cassava compared to independently fitted WNLS models.

Additional key words: simultaneous modeling system; tree biomass-carbon; weighted non-linear-SUR.

Abbreviations used: A (tree's age); AGB (aboveground biomass); AGC (aboveground carbon); AIC (Akaike information criterion); BA (basal area per hectare); Bba (dry biomass of bark); Bbr (dry biomass of branches); Ble (dry biomass of leaves); Bst (dry biomass of stem); CA (crown area of the trees sampled); Cba (carbon content of tree bark); Cbr (carbon content of tree branches); CD (crown diameter in two cardinal directions, N-S and E-W); CF (average carbon fraction); Cle (carbon content of tree leaves); Cst (carbon content of tree stem); D (diameter at breast height); Dg (quadratic mean diameter); H (tree height); Hg (height of the tree with Dg); LOOCV (leave-one-out-cross validation); MAPE (mean absolute percent error); Nplant (planting density); Nstem (number of stems per ha); Nstemplant (average numbers of stems per plant); RMSE (root mean square error); SUR (seemingly unrelated regression); WD (wood density); WNLS (weighted nonlinear least-squares); WNSUR (weighted nonlinear seemingly unrelated regression).

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Introduction

Litsea glutinosa (Lour.) C. B. Rob. belongs to the *Lauraceae* family and is a small to medium-sized tree species that grows naturally throughout Asia (Heuze et al., 2015; Hinsinger & Strijk, 2016; Useful Tropical Plants, 2021). In the Central Highlands of Vietnam, this species is distributed in tropical evergreen broadleaf forests and is widely planted in combination with cassava (*Manihot esculenta* Crantz) in the agroforestry model on fallow land of ethnic minorities (Huy, 2009a, 2009b, 2014). In this agroforestry model, *L. glutinosa* provides valuable biomass to the industry, especially valuable stem bark, and contributes to ecosystem services such as sequestering CO_2 (Huy, 2009a, 2009b, 2014).

L. glutinosa is a fast-growing multi-purpose plant. Its bark contains essential oils used in the pharmaceutical industry (Heuze et al., 2015), industrial glues, and manufacturing paints (Tiwari et al., 2010). Bark extract is used as an ingredient in commercial cosmetic preparations such as a skin conditioner (Useful Tropical Plants, 2011) and incense for religious services. Its golden brown hardwood is used for furniture and paper manufacturing. Additionally, wood and bark contain gluten and are used as binders (Useful Tropical Plants, 2021). Its leaves are used as fodder for livestock. The medicinal value of *L. glutinosa* has been mentioned in many studies. Its root bark is anti-inflammatory (Wua et al., 2017), stem bark is an antidiarrheal (Sumithregowda et al., 2017), and *L. glutinosa* is also used to treat joint and back pain (Pandey & Mandal, 2012). Among the different components, the biomass of the stem bark of *L. glutinosa* has the highest value (Huy, 2009a, 2009b; Mulia & Nguyen, 2021). Therefore, *L. glutinosa* is also considered one of the most important non-timber forest tree species in many countries such as Vietnam and India (Mohammad et al., 2020).

The agroforestry model with *L. glutinosa* and cassava is easy to grow, does not require intensive care, and provides various products from forest trees and agricultural crops. Therefore, it is suitable for the farming practices of ethnic minorities in tropical highlands. On the other hand, planting this tree species in agroforestry models also plays an important role in absorbing CO_2 to mitigate the greenhouse effect (Mulia & Nguyen, 2021). Therefore, there is a demand to develop a modeling system for *L. glutinosa* species to estimate individual tree biomass and the carbon sequestration potential of this species in an agroforestry system.

Allometric equations have usually been developed to estimate the biomass of aboveground components, including stem, branches, leaves, bark, and the total aboveground biomass (*AGB*). Although biomass components are sometimes modeled independently of each other, the tree parts and the tree total biomass are biologically related (Huy et al., 2019). Therefore, component models are best fitted simultaneously with the model for *AGB* as a system of equations using Seemingly Unrelated Regression (SUR) (Parresol, 2001). SUR accounts for the cross-equation correlation and helps reduce the variability of the parameters and increase the reliability of the biomass estimation of tree parts and totals (Poudel & Temesgen, 2016; Kralicek et al., 2017; Huy et al., 2019; Trautenmüller et al., 2021). The relationship between biomass components and common dendrometric variables (diameter at breast height (D), and tree height (H)) is nonlinear and the residuals are heteroscedastic. Therefore, applying the weighted nonlinear seemingly unrelated regression (WNSUR) method can further improve the reliability of the estimates of *AGB* and its components (Trautenmüller et al., 2021).

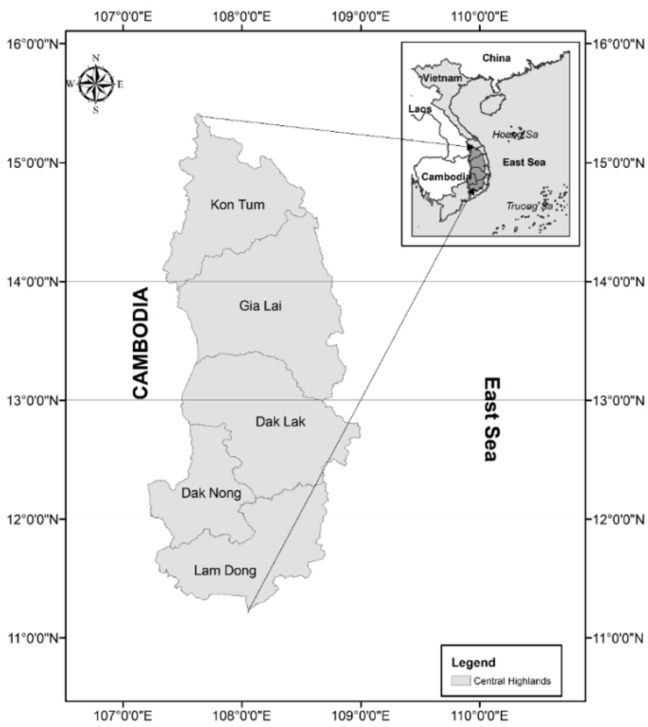

Figure 1. Location of the study in the tropical Central Highlands of Vietnam.

The objectives of this study were to develop and cross-validate the simultaneous modeling systems for estimating components and total tree biomass and carbon of *L. glutinosa* in an agroforestry model with cassava. We hypothesized that simultaneous estimation of these attributes using WNSUR provides improved and reliable biomass and carbon estimates compared to independently fitted models. We used the dataset derived from a technical report (Huy, 2009a) and applied it to a new methodology to improve biomass and carbon estimates for this studied species in the agroforestry model.

Material and methods

Study sites and agroforestry model studied

The study area is in the Central Highlands of Vietnam (Fig. 1). The average annual temperature is 21.6^{0}C and

Table 1. Summary statistics of forest stand factors in the studied agroforestry model, based on 22 sample plots located in the agroforestry model.

Variables[1]	Min.	Mean	Max.	Std.
BA (m^2 ha^{-1})	0.40	3.03	7.33	2.17
Dg (cm)	1.0	4.4	7.0	1.9
Hg (m)	1.6	3.4	5.4	1.1
Origin of the plant (1, from seed; 2, from the shoot)	1.0	1.3	2.0	0.5
Nplant (no. of plants ha^{-1})	500	1322	1967	400
Nstem (no. of stems ha^{-1})	500	2268	5900	1299
Nstemplant (no. of stems per plant averaged)	1.0	1.7	3.4	0.9
Number of cycles	1.0	1.4	3.0	0.6

[1] *BA*: basal area per hectare; *Dg*: quadratic mean diameter; *Hg*: height of the tree with *Dg*.

the average annual rainfall is 2,213 mm (Hydro-meteorological Station in the Central Highlands). Located at an altitude of 400-800 m above sea level, the soil types in the study area include red-brown soil on basalt, gray soil, and red-yellow soil on granite.

The studied agroforestry model includes the native multi-purpose tree species *L. glutinosa* combined with cassava. *L. glutinosa* is combined in different proportions with cassava ranging from 50% to 80% of the agroforestry area and is managed in a 6-7 year rotation cycle. Planting density (*Nplant*) ranged from 500 to 1967 plants ha^{-1}. *L. glutinosa* was grown from seeds collected at local tropical evergreen broadleaf forests in the first rotation, and in the following cycles, regenerated stems from coppice were used. The average number of stems $plant^{-1}$ (*Nstemplant*) in the second and third cycles ranged from 1 to 3.4. The number of stems ha^{-1} (*Nstem*) ranged from 500 to 5900. After the third cycle, *L. glutinosa* was replanted from seeds (Table 1).

Sampling design, data collection, and variable calculation

Twenty-two 300-m^2 circular plots were sampled covering a full range of ages (*A*) (1-7 years), a range of planting density, and a range of rotation cycles 1-3 in the agroforestry model. For all trees in the sample plots *D* (cm), *H* (m), and the *Nstemplant* were recorded. In each sample plot, one selected tree having the same *D* as the quadratic mean diameter (*Dg*), was destructively sampled to obtain a tree dry biomass/carbon dataset and its components. Age distributions of all sampled plots and destructively sampled trees are shown in Fig. 2. Before felling the sample tree, *D, H*, and crown diameter (*CD*, m) in two cardinal directions, North-South and East-West, and the sampled tree's age (*A*, year) were recorded. The crown area of the trees sampled (*CA*, m^2) was calculated by the formula $CA = \frac{\pi}{4} \times \overline{CD}^2$, where $\overline{CD}$ (the average crown diameter) was obtained from two cardinal direction

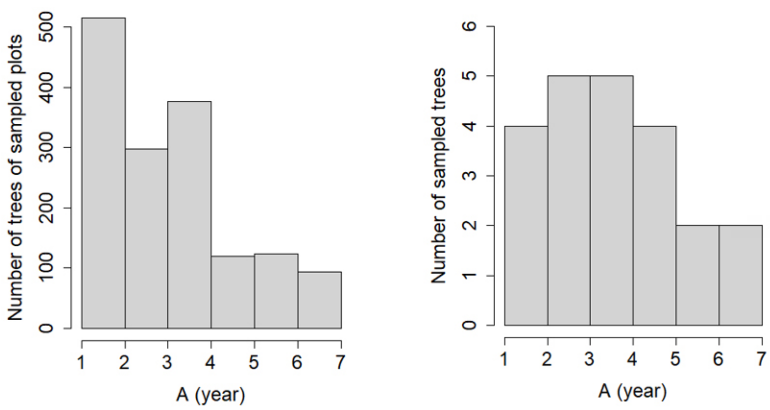

Figure 2. Tree age distributions in the 22 sampled plots (left) and destructively sampled trees (right).

Table 2. Summary statistics of tree variables, based on a dataset of n = 22 destructively sampled trees in 22 sample plots located in the agroforestry model.

Variables[1]	Min.	Mean	Max.	Std.
D (cm)	1.0	4.4	7.0	1.9
H (m)	1.6	3.4	5.4	1.1
A (year)	1.0	3.9	7.0	1.7
CA (m^2 $stem^{-1}$)	0.79	2.53	7.07	1.28
Bst (kg $tree^{-1}$)	0.132	1.765	4.479	1.376
Bbr (kg $tree^{-1}$)	0.040	0.697	1.656	0.472
Ble (kg $tree^{-1}$)	0.080	0.832	1.885	0.501
Bba (kg $tree^{-1}$)	0.031	0.548	1.356	0.428
AGB (kg $tree^{-1}$)	0.283	3.844	8.703	2.687
Cst (kg $tree^{-1}$)	0.060	0.846	2.156	0.653
Cbr (kg $tree^{-1}$)	0.019	0.331	0.793	0.224
Cle (kg $tree^{-1}$)	0.037	0.405	0.917	0.243
Cba (kg $tree^{-1}$)	0.014	0.250	0.613	0.195
AGC (kg $tree^{-1}$)	0.130	1.834	4.187	1.275

[1] *Bst/Cst, Bbr/Cbr, Ble/Cle, Bba/Cba* and *AGB/AGC* are biomass/carbon of stem, branches, leaves, bark and total tree aboveground biomass/carbon, respectively. *A*: age of the plant. *CA*: crown area. *D*: diameter at breast height. *H*: height of the sampled tree.

measurements. After felling, tree heights were remeasured and fresh weights of the stem, branches, leaves, and bark were recorded. The four sampled tree components including stem, bark, branches and leaves were separated and weighed for fresh biomass in the field using a scale with a precision of 0.01 kg. Stem wood and bark samples were obtained from the base, middle, and top sections of the sampled tree. Sampled branches included small and large branches, and the sampled leaves on these branches. For four sampled tree components, a total of 88 samples were collected for the analysis; 100-300 g of each sample was weighed for fresh biomass on site using an electronic scale with a precision of 0.01 g.

The sample materials were dried at 105°C until a constant weight was attained. This provided the average fresh-to-dry mass ratio for all tree components to calculate the respective dry biomass – stem (*Bst*, kg $tree^{-1}$), branches (*Bbr*, kg $tree^{-1}$), leaves (*Ble*, kg $tree^{-1}$), and bark (*Bba*, kg $tree^{-1}$). Total tree aboveground biomass was computed as the sum of component biomass i.e., $AGB = Bst + Bbr + Ble + Bba$ (kg $tree^{-1}$). The samples were analyzed after drying and the percentage of carbon was estimated by the

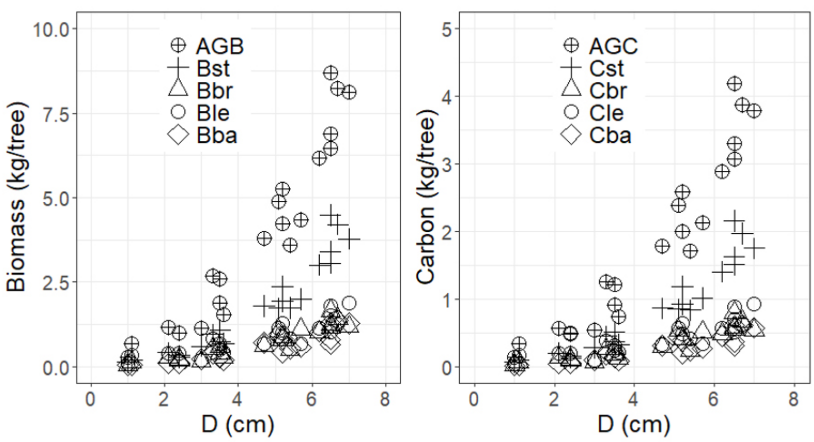

Figure 3. Scatter plot of biomass and carbon vs. *D* for tree stem (*Bst/Cst*, kg), branches (*Bbr/Cbr*, kg), leaves (*Ble/Cle*, kg), bark (*Bba/Cba*, kg), and total tree aboveground biomass/carbon (*AGB/AGC*, kg).

Walkley & Black method (1934) and the carbon content of tree stem (*Cst*, kg tree^{-1}), branches (*Cbr*, kg tree^{-1}), leaves (*Cle*, kg tree^{-1}), bark (*Cba*, kg tree^{-1}), and the total tree aboveground carbon (*AGC = Cst + Cbr + Cle + Cba*, kg tree^{-1}) was calculated. Table 2 shows the summary statistics for each tree predictor and the destructively sampled tree response variables.

Statistical analysis

In this study, we compared two methods to fit systems of equations for *AGB/AGC* and their components: weighted nonlinear least-squares (WNLS) and weighted nonlinear seemingly unrelated regression (WNSUR) fit by the generalized least squares method.

— *Relationship among tree biomass-carbon components and selection of predictors:* The factor analysis method was performed to examine the relationship among the tree biomass and carbon components and select their predictors from *D, H, A,* and *CA* (Kim & Mueller, 1978; DeCoster, 1998). This method supports both principal components and classical factor analysis, which produces a linear combination of multiple quantitative variables and explains the largest percentage variation among those variables. The values of the variables were standardized by subtracting their means and dividing by their standard deviations.

— *Model calibration – Independent fit:* Fig. 3 shows that the relationship between tree biomass-carbon components, *AGB* and *AGC* vs. *D* conforms to the power law that was used in the study. Preliminary analysis showed that power models fit by the nonlinear method produced higher reliability than the log-linear model. This is consistent with previous studies (Huy et al., 2016a, 2016b, 2016c). Therefore, we used the nonlinear method to fit biomass-carbon modeling systems, and the heteroscedasticity in residuals was accounted for by using appropriate weighting (Davidian & Giltinan, 1995; Picard et al., 2012; Huy et al., 2016a, 2016b, 2016c, 2019). The WNLS models were fitted using nls function in the statistical software R (R Core Team, 2021). The model forms used were as follows:

$$\mathrm{Y}_i = \mathrm{aX}_i^{\,b} + \varepsilon_i \tag{1}$$

$$\varepsilon_i \sim iid\ \mathcal{N}(0, \sigma_i^2) \tag{2}$$

where Y_i is the *Bst/Cst*, *Bbr/Cbr*, *Ble/Cle*, *Bba/Cba* or *AGB/AGC* in kg for the i^{th} sampled tree; *a* and *b* are the parameters of the model; X_i is the predictor(s) selected by factor analysis such as a combination of *D* (cm), *H* (m), *A* (year), D^2H for the i^{th} sampled tree; and ε_i is the random error associated with the i^{th} sampled tree. The weighting variable is $1/D^{\delta}$ or $1/(D^2H)^{\delta}$ and δ is selected in a range of ±2 (Picard et al., 2012).

— *Model calibration – Simultaneous estimation:* Independently fitted component models do not ensure that the *AGB/AGC* calculated as the sum of predicted tree component models is the same as the *AGB/AGC* estimated from independently developed *AGB/AGC* models (Sanquetta et al., 2015; Affleck & Dieguez-Aranda, 2016; Poudel & Temesgen, 2016; Gonzalez-Benecke et al., 2018; Huy et al., 2019; Trautenmüller et al., 2021). The SUR can solve that limitation by allowing simultaneous estimation of the tree biomass or carbon component and *AGB/AGC* (Parresol, 2001). Additionally, different weighting factors can be used for each equation to account for heteroscedasticity. The WNSUR models were fitted using SAS procedure Proc Model (SAS Inst., 2014) with the generalized least squares method. The modeling systems for the component and total tree biomass and carbon had the following general forms:

$$\textit{Stem: } Bst/Cst = a_1 X_{1j}^{\,b1j} + \varepsilon_1 \tag{3}$$

$$\textit{Branches: } Bbr/Cbr = a_2 X_{2i}^{\,b_{2}j} + \varepsilon_2 \tag{4}$$

$$\textit{Leaves: } Ble/Cle = a_3 X_{3j}^{\,b3j} + \varepsilon_3 \tag{5}$$

$$\textit{Bark: } Bba/Cba = a_4 X_{4j}^{\,b4j} + \varepsilon_4 \tag{6}$$

$$AGB/AGC = Bst/Cst + Bbr/Cbr + Ble/Cle + Bba/Cba = a_1 X_{1i}^{\,b1j} + a_2 X_{2j}^{\,b_2j} + a_3 X_{3j}^{\,3j} + a_4 X_{4j}^{\,4j} + \varepsilon_5 \tag{7}$$

where *Bst/Cst*, *Bbr/Cbr*, *Ble/Cle*, *Bba/Cba* and *AGB/AGC* are biomass/carbon of stem, branches, leaves, bark, and total in kg, respectively; a_i and b_i are parameters of the power model *i* (*i* = 1, 2, 3, 4 for the stem, branches, leaves, and bark respectively); X_{ij} is the predictor variables (*D, H,* D^2HWWD) for the i^{th} equation and the j^{th} predictor; and ε_i is the residuals for the i^{th} equation (*i* = 1, 2, 3, 4, 5). The weighting variable is $1/D^{\delta}$ *or* $1/(D^2H)^{\delta}$ and δ is selected in a range of ±2 (Picard et al., 2012).

Cross-validation

Leave-one-out cross validation (LOOCV) is a special case of K-fold cross-validation, where K is set to the number of samples in the dataset. LOOCV has the maximum computational cost. It requires that one model be created and evaluated for each sample in the dataset (Cheng et al., 2017). LOOCV was applied for the cross-validation of modeling systems. The dataset was split into two parts with n-1 samples for model development and one for cross-validation. The process was repeated for all the observations, and the error statistics were computed at each iteration and averaged over the number of iterations.

The Akaike Information Criterion (AIC) (Akaike, 1973) compares and selects the best model. The adjusted R^2 describes the variability in the dependent variable ex-

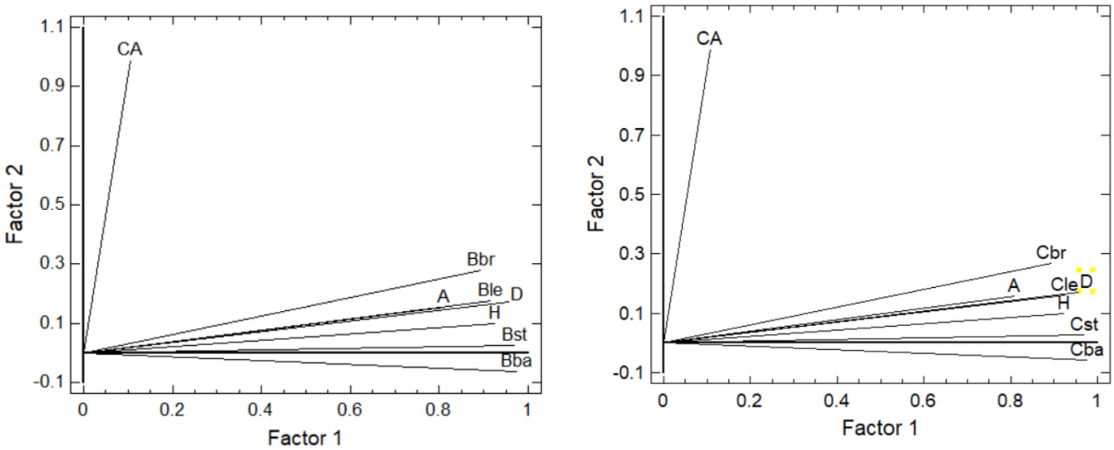

Figure 4. The plot of Factor 1 vs. Factor 2 of the Factor Analysis. Left: Tree biomass components (*Bst*, *Bbr*, *Ble* and *Bba*) along with tree predictors (*D, H, A*, and *CA*). Right: Tree carbon sequestration components (Cst, Cbr, Cle and Cba) and tree predictors (*D, H, A*, and *CA*). The factor plots show the location of each variable; the variables furthest from the reference lines at 0 make the largest contribution to the factors, and the variables located close to each other are closely related.

plained by the set of predictors accounting for the number of predictors used in the model, whereas the diagnostic plots are used to examine residuals for any departure from model assumptions. The lower the AIC and the closer the adj. R^2 is to 1, the better the model. At the same time, cross-validation errors based on each sample such as bias (%), root mean square error (RMSE, kg tree^{-1}), and mean absolute percent error (MAPE, %) were used and averaged over the n realizations of LOOCV. The models with the smallest values of cross-validation errors were preferred.

$$Bias\ (\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{y_i - \hat{y}_i}{y_i} \quad (8)$$

$$RMSE\ (\text{kg}\ tree^{-1}) = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(y_i - \hat{y}_i)^2} \quad (9)$$

$$MAPE\ (\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \quad (10)$$

where n is the number of realizations (number of samples); and y_i and $\hat{y}_i$ are observed and predicted *Bst/Cst, Bbr/Cbr, Ble/Cle, Bba/Cba* and *AGB/AGC* for the ith realization, respectively.

Bias and MAPE statistics estimated using Eqs. (8) and (10) have been the most widely used by many authors (e.g., Chave et al., 2005; Basuki et al., 2009; Huy et al., 2019, 2022). In some cases, the errors based on Eqs. (8) and (10) tend to be biased on negative errors, $y_i < \hat{y}_i$ than in positive errors; therefore, the average systematic error (ASE) and the mean percent standard error (MPSE) were used (Zeng et al., 2017). The only difference among these metrics is the denominator; that is, instead of the observed value, the predicted value of the response is used in the denominator (Zeng et al., 2017; Huy et al., 2022).

Results

Relationships among tree biomass, carbon components, and predictors

Factor analysis was carried out with two groups of eight variables each. Group 1 included tree biomass components (*Bst, Bbr, Ble,* and *Bba*) and tree-level predictors (*D, H, A,* and *CA*) and group 2 included tree carbon components (*Cst, Cbr, Cle* and *Cba*) and tree predictors (*D, H, A* and *CA*). Factor analysis provided a small number of factors that account for most of the variability in the eight variables and supported an examination of the relationship between biomass and carbon components of trees. In both groups, two factors were extracted since two factors had eigenvalues greater than or equal to 1.0. Together, they accounted for 89.24% (group 1) and 89.30% (group 2) of the variability in the original data.

According to the results of the factor analysis, there were strong relationships between tree biomass and carbon components and tree predictors (*D, H, A*). They were placed close together in Fig. 4. They had a high coefficient (over 0.83) while *CA* had the lowest coefficient (below 0.30), which was shown in the first common factor equations (Factor 1) below. *CA* was excluded from further analysis because of its negligible influence on the biomass and carbon of the tree components.

The first common factor equations for tree biomass/carbon components are:

$$Factor\ 1 = 0.96088 \times Bst + 0.95130 \times Bba + 0.93313 \times Ble + 0.92899 \times Br + 0.82619 \times A + 0.97296 \times D + 0.92957 \times H + 0.27349 \times CA \quad (11)$$

$$Factor\ 1 = 0.96183 \times Cst + 0.953593 \times Cba + 0.939325 \times Cle + 0.927541 \times Cbr + 0.825706 \times A + 0.972641 \times D + 0.928428 \times H + 0.272406 \times CA \quad (12)$$

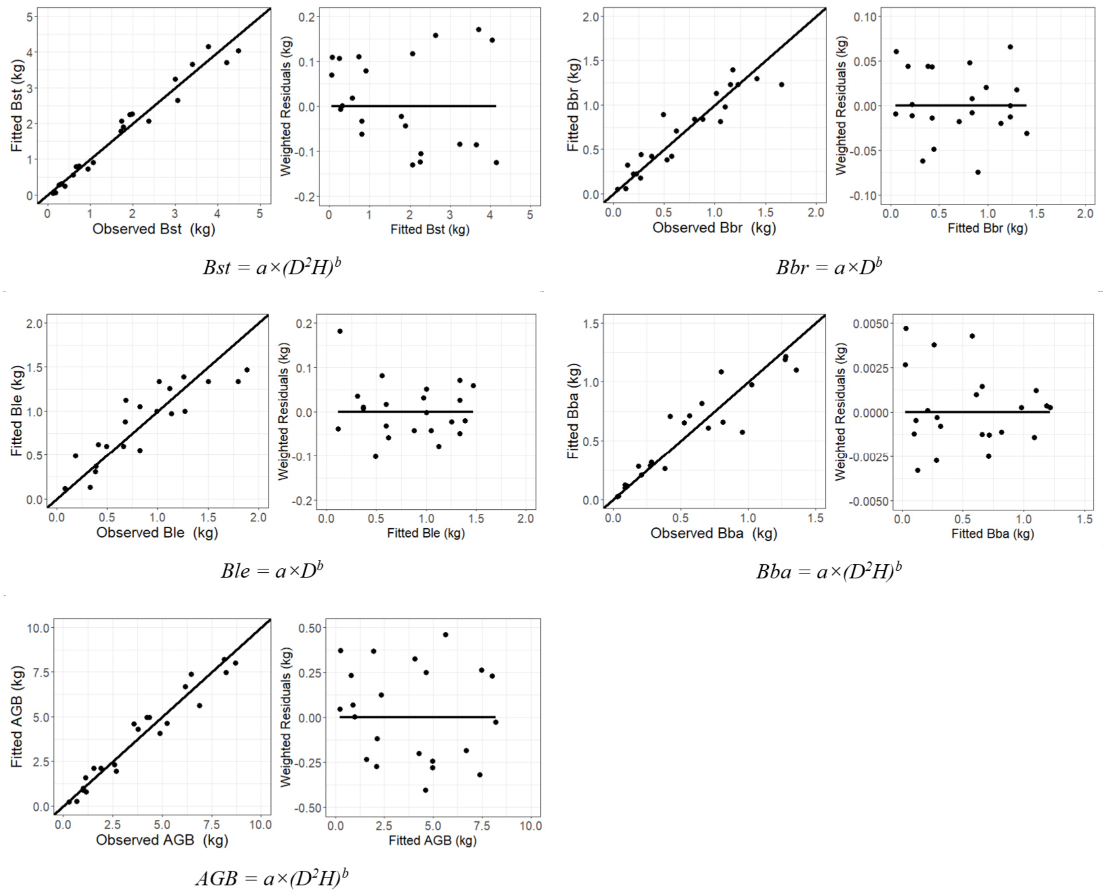

Figure 5. Plots of selected weighted non-linear models of tree biomass components B*st, Bbr, Ble* and *Bba* (biomass of stem, branches, leaves, and bark, respectively) and total tree aboveground biomass (*AGB*) developed separately: Right: Fitted vs. Observed values; Left: Weighted residuals vs. Fitted values.

Independently fit models

The results for selecting independent models using the WNLS method for tree biomass and carbon components and *AGB/AGC* vs. different combinations of variables *D, H,* and D^2H by LOOCV are presented in Tables 3 and 4. We also observed that tree age (*A*) was marginally significant for all components and total ($p > 0.05$). The selected models from the independent fitting of component and total *AGB* and *AGC* were as follows:

$$Bst/Cst = a \times (D^2H)^b \tag{13}$$

$$Bbr/Cbr = a \times D^b \tag{14}$$

$$Ble/Cle = a \times D^b \tag{15}$$

$$Bba/Cba = a \times (D^2H)^b \tag{16}$$

$$AGB/AGC = a \times (D^2H)^b \tag{17}$$

The plots of observed vs. fitted values and weighted residuals vs. the fitted values (Fig. 5) depict a good model fit for independent fitting of component and total biomass. The results also showed that the model selection retained identical predictors or a combination of predictors when independent tree biomass and carbon components models were fitted (Table 3 and Table 4).

The carbon fraction of the tree species studied

The results of calculating the average carbon fraction (CF = Carbon/Biomass weight) for tree biomass components and total and the variation within the 95% confidence range are shown in the box plot in Fig. 6.

Simultaneous modeling

The tree age was excluded from further analysis based on the results of independently fit models. Sixteen WNSUR equation systems were developed using *D, H*, and their combinations as predictors to predict *AGB, AGC,* and their components (Tables S1 and S2 [suppl]). Unlike the independent model fit, the results showed that the model

Table 3. Leave-One-Out Cross Validations (LOOCV) to select separate weighted nonlinear equations along with different combinations of tree predictor(s) for biomass components including *Bst, Bbr, Ble* and *Bba* (biomass of stem, branches, leaves and bark, respectively) and total tree aboveground biomass (*AGB*).

Model form	Weight variable	AIC	Adj. R^2	Bias (%)	RMSE (kg)	MAPE (%)
$Bst = a \times D^b$	$1/D$	12.9	0.925	9.0	0.293	22.9
$Bst = a \times D^b \times H^c$	$1/D$	3.0	0.956	5.9	0.269	19.3
$Bst = a \times (D^2H)^b$	**$1/(D^2H)^{0.2}$**	**3.8**	**0.958**	**6.4**	**0.238**	**18.2**
$Bst = a \times D^b \times A^{c*}$	$1/D$	14.1	0.923	4.0	0.306	23.3
$Bst = a \times D^b \times H^c \times A^{d*}$	$1/D$	4.7	0.953	5.4	0.286	19.7
$Bst = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	1.2	0.945	-1.7	0.245	19.4
$Bbr = a \times D^b$	**$1/D$**	**-14.1**	**0.842**	**-8.3**	**0.141**	**29.7**
$Bbr = a \times D^b \times H^{c*}$	$1/D$	-15.2	0.867	-6.1	0.143	30.0
$Bbr = a \times (D^2H)^b$	$1/(D^2H)$	-10.7	0.767	-13.9	0.161	34.5
$Bbr = a \times D^b \times A^{c*}$	$1/D$	-12.2	0.832	-8.8	0.151	30.9
$Bbr = a \times D^b \times H^{c*} \times A^{d*}$	$1/D$	-13.3	0.859	-6.5	0.150	31.1
$Bbr = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	-8.8	0.747	-14.7	0.173	36.2
$Ble = a \times D^b$	**$1/D^\delta$**	**1.1**	**0.732**	**-11.4**	**0.214**	**34.5**
$Ble = a \times D^b \times H^{c*}$	$1/D$	2.5	0.721	-11.5	0.240	37.5
$Ble = a \times (D^2H)^b$	$1/(D^2H)$	8.9	0.702	-18.1	0.213	39.6
$Ble = a \times D^b \times A^{c*}$	$1/D$	2.9	0.720	-11.4	0.229	36.0
$Ble = a \times D^b \times H^{c*} \times A^{d*}$	$1/D$	4.3	0.710	-12.1	0.259	39.6
$Ble = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	10.5	0.668	-18.7	0.234	42.0
$Bba = a \times D^b$	$1/D$	-15.8	0.797	-7.7	0.148	30.0
$Bba = a \times D^b \times H^{c*}$	$1/D$	-18.9	0.837	-7.3	0.124	24.0
$Bba = a \times (D^2H)^b$	**$1/(D^2H)$**	**-29.9**	**0.844**	**-6.4**	**0.119**	**24.0**
$Bba = a \times D^b \times A^c$	$1/D$	-20.1	0.840	-3.9	0.135	29.9
$Bba = a \times D^b \times H^c \times A^d$	$1/D$	-26.9	0.897	-2.1	0.125	27.1
$Bba = a \times (D^2H)^b \times A^c$	$1/(D^2H)$	-33.4	0.889	-4.1	0.115	26.1
$AGB = a \times D^b$	$1/D$	43.8	0.925	1.3	0.556	20.9
$AGB = a \times D^b \times H^{c*}$	$1/D$	42.2	0.934	1.8	0.640	21.3
$AGB = a \times (D^2H)^b$	**$1/(D^2H)^{0.2}$**	**42.7**	**0.934**	**1.8**	**0.589**	**20.1**
$AGB = a \times D^b \times A^{c*}$	$1/D$	45.6	0.922	1.5	0.590	21.6
$AGB = a \times D^b \times H^c \times A^{d*}$	$1/D$	43.8	0.932	2.0	0.695	22.7
$AGB = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	45.9	0.912	-5.2	0.684	23.0

In LOOCV, the dataset was split into n-1 samples used for developing models, the remaining one sample used for validation, calculation of AIC, Adj. R2, Bias, RMSE, MAPE; finally, all of those statistics averaged over n realizations. *: parameter with p > 0.05. In bold, models selected based on LOOCV statistics and diagnostic plots.

selection retained the different predictors or a combination of predictors when these models were fit simultaneously. Based on the errors statistics of LOOCV, we found two optimal combinations of tree predictors for simultaneous modeling systems for tree biomass and carbon components and the totals are as follows:

$$Bst = a_1 \times D^{b1} \tag{18}$$

$$Bbr = a_2 \times D^{b2} \tag{19}$$

$$Ble = a_3 \times D^{b3} \tag{20}$$

$$Bba = a_4 \times (D^2H)^{b4} \tag{21}$$

$$AGB = Bst + Bbr + Ble + Bba = a_1 \times D^{b1} + a_2 \times D^{b2} + a_3 \times D^{b3} + a_4 \times (D^2H)^{b4} \tag{22}$$

$$Cst = a_1 \times (D^2H)^{b1} \tag{23}$$

$$Cbr = a_2 \times D^{b2} \tag{24}$$

Table 4. Leave-One-Out Cross Validations (LOOCV) to select separate weighted nonlinear equations along with different combinations of tree predictor/s for carbon components including *Cst, Cbr, Cle* and *Cba* (carbon sequestration of stem, branches, leaves and bark, respectively) and total tree aboveground carbon *(AGC)*.

Model form	Weight variable	AIC	Adj. R^2	Bias (%)	RMSE (kg)	MAPE (%)
$Cst = a \times D^b$	$1/D$	-18.6	0.924	3.5	0.135	22.2
$Cst = a \times D^b \times H^c$	$1/D$	-26.2	0.950	4.9	0.134	19.4
$Cst = a \times (D^2H)^b$	**$1/(D^2H)$**	**-30.1**	**0.946**	**-1.6**	**0.118**	**19.6**
$Cst = a \times D^b \times A^{c*}$	$1/D$	-17.7	0.925	3.0	0.146	22.8
$Cst = a \times D^b \times H^c \times A^{d*}$	$1/D$	-24.9	0.949	4.3	0.142	19.8
$Cst = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	-29.4	0.943	-1.8	0.121	19.2
$Cbr = a \times D^b$	**$1/D$**	**-44.1**	**0.830**	**-9.0**	**0.067**	**29.8**
$Cbr = a \times D^b \times H^{c*}$	$1/D$	-45.3	0.859	-6.7	0.069	30.6
$Cbr = a \times (D^2H)^b$	$1/(D^2H)$	-40.9	0.752	-14.2	0.077	34.4
$Cbr = a \times D^b \times A^{c*}$	$1/D$	-42.2	0.819	-9.5	0.072	31.2
$Cbr = a \times D^b \times H^{c*} \times A^{d*}$	$1/D$	-43.5	0.850	-7.1	0.074	31.9
$Cbr = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	-38.9	0.735	-15.1	0.083	36.4
$Cle = a \times D^b$	**$1/D$**	**-29.9**	**0.741**	**-10.9**	**0.100**	**33.9**
$Cle = a \times D^b \times Hc*$	$1/D$	-28.5	0.735	-11.3	0.113	37.2
$Cle = a \times (D^2H)^b$	$1/(D^2H)$	-21.6	0.715	-18.2	0.101	39.6
$Cle = a \times D^b \times A^{c*}$	$1/D$	-28.0	0.732	-10.8	0.108	35.5
$Cle = a \times D^b \times H^{c*} \times A^{d*}$	$1/D$	-26.8	0.726	-11.8	0.123	39.5
$Cle = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	-19.9	0.685	-18.9	0.112	42.4
$Cba = a \times D^b$	$1/D$	-48.9	0.798	-7.5	0.066	29.0
$Cba = a \times D^b \times H^{c*}$	$1/D$	-51.7	0.834	-7.0	0.056	23.2
$Cba= a \times (D^2H)^b$	**$1/(D^2H)$**	**-62.3**	**0.842**	**-6.3**	**0.053**	**22.9**
$Cba = a \times D^b \times A^c$	$1/D$	-52.1	0.831	-4.2	0.062	29.1
$Cba = a \times D^b \times H^c \times A^d$	$1/D$	-57.4	0.882	-2.7	0.060	27.0
$Cba = a \times (D^2H)^b \times A^c$	$1/(D^2H)$	-65.5	0.878	-4.3	0.054	26.0
$AGC = a \times D^b$	$1/D$	13.2	0.922	0.8	0.273	20.8
$AGC = a \times D^b \times H^{c*}$	$1/D$	12.2	0.929	1.3	0.316	21.2
$AGC= a \times (D^2H)^b$	**$1/(D^2H)^{0.2}$**	**13.0**	**0.929**	**0.9**	**0.292**	**20.1**
$AGC = a \times D^b \times A^{c*}$	$1/D$	15.0	0.918	0.9	0.293	21.7
$AGC = a \times D^b \times H^{c*} \times A^{d*}$	$1/D$	14.0	0.926	1.4	0.344	22.6
$AGC = a \times (D^2H)^b \times A^{c*}$	$1/(D^2H)$	15.6	0.910	-5.4	0.331	23.5

In LOOCV, the dataset was split into n-1 samples used for developing models, the remaining one sample used for validation, calculation of AIC, Adj. R2 Bias, RMSE, MAPE; finally, all of those statistics averaged over n realizations. *: Parameter with $p > 0.05$. In bold, models selected based on LOOCV statistics and diagnostic plots.

$$Cle = a_3 \times (D^2H)^{b3} \tag{25}$$

$$Cba = a_4 \times (D^2H)^{b4} \tag{26}$$

$$AGC = Cst + Cbr + Cle + Cba = a_1 \times (D^2H)^{b1} + a_2 \times D^{b2} + a_3 \times (D^2H)^{b3} + a_4 \times (D^2H)^{b4} \tag{27}$$

The parameters of the two selected simultaneous modeling systems that were fit by the WNSUR method using the entire dataset are presented in Table 5. In addition to the simplicity of application, since measuring tree *H* is costly, two modeling systems for simultaneously predicting tree biomass and carbon were created with only *D* (Table 6).

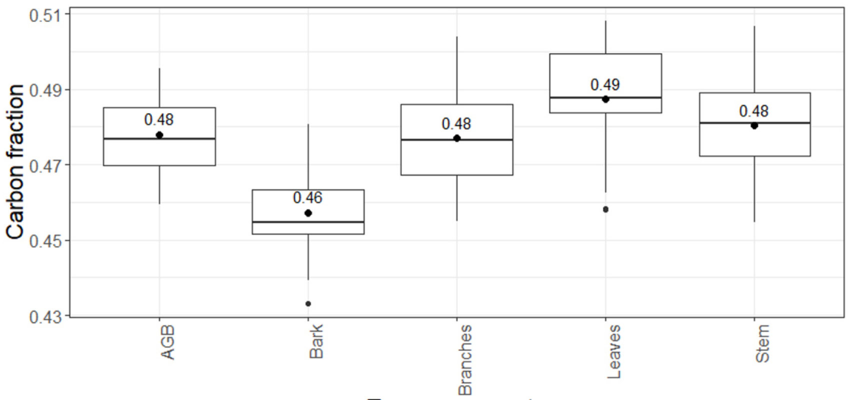

Figure 6. Box plot of carbon fraction (CF) by total tree aboveground biomass (AGB) and its components. Points and numbers within the boxplots represent the means of CF for the tree components and the total. Sample size n = 22.

Both WNLS and WNSUR addressed the issue of heteroscedasticity of the residuals. The WNLS residuals fluctuated uniformly along with the fitted values of the models, whereas the WNSUR model reduced the variability of the residuals significantly compared to the WNLS model (Fig. 7). The result of comparison of LOOCV statistics between two methods of independent WNLS and simultaneous WNSUR to fit selected *AGB* and *AGC* models is shown in Table 7.

Discussion

Predictors and the variation of tree biomass-carbon components

Tree age (*A*) was insignificant in tree parts and total biomass and carbon models (Tables 3 and 4). Therefore, variables *D* and *H* (Dutca et al., 2018) may be sufficient to describe the variability in biomass and carbon in *Lit-*

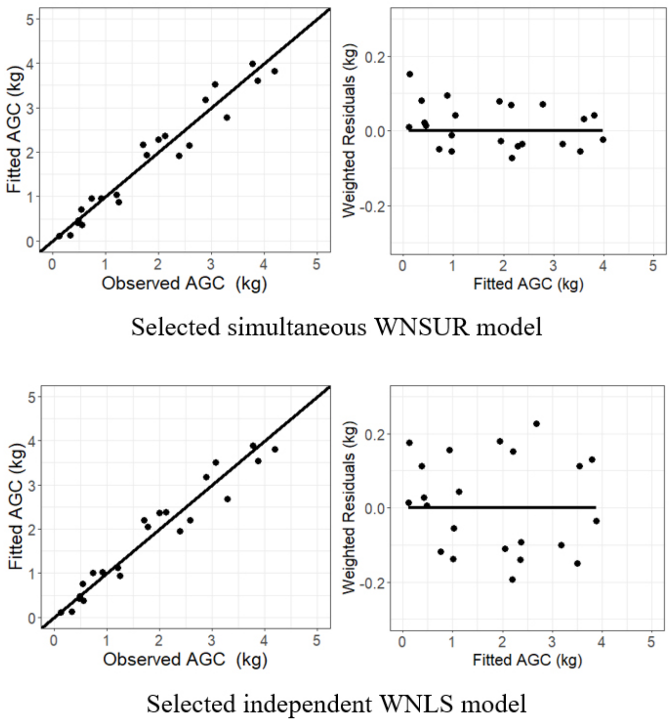

Figure 7. Plots of fitted vs. observed AGC (left) and weighted residuals vs. fitted AGC (right) for the model fitted with the entire dataset. Comparison of two methods of independent weighted non-linear (WNLS) and simultaneous weighted non-linear SUR (WNSUR).

Table 5. Model equations and estimated parameters of the selected modeling systems for simultaneous estimation of *AGB/AGC* and its components using the WNSUR method (based on the entire dataset).

Prediction of tree AGB or AGC and its components	Parameters	Estimate ± Std. Error	RMSE (kg tree^{-1})	Adj. R^2
***AGB* and its components**				
$Bst = a_1 \times D^{b1}$	a_1	0.03203 ± 0.01450	0.349	0.936
	b_1	2.50566 ± 0.24550		
$Bbr = a_2 \times D^{b2}$	a_2	0.04571 ± 0.02050	0.173	0.865
	b_2	1.75896 ± 0.24880		
$Ble = a_3 \times D^{b3}$	a_3	0.07274 ± 0.03410	0.238	0.774
	b_3	1.57179 ± 0.25980		
$Bba = a_4 \times (D^2H)^{b4}$	a_4	0.01545 ± 0.00766	0.156	0.867
	b_4	0.80636 ± 0.09310		
$AGB = Bst + Bbr + Ble + Bba$			0.692	0.934
***AGC* and its components**				
$Cst = a_1 \times (D^2H)^{b1}$	a_1	0.01399 ± 0.00367	0.134	0.956
	b_1	0.91022 ± 0.05050		
$Cbr = a_2 \times D^{b2}$	a_2	0.01514 ± 0.00685	0.087	0.847
	b_2	1.97080 ± 0.24890		
$Cle = a_3 \times (D^2H)^{b3}$	a_3	0.05770 ± 0.02160	0.113	0.782
	b_3	0.46021 ± 0.04530		
$Cba = a_4 \times (D^2H)^{b4}$	a_4	0.00702 ± 0.00342	0.071	0.866
	b_4	0.80219 ± 0.09160		
$AGC = Cst + Cbr + Cle + Cba$			0.328	0.934

Bst/Cst, Bbr/Cbr, Ble/Cle, Bba/Cba and *AGB/AGC* are biomass/carbon of stem, branches, leaves, bark and total aboveground biomass/carbon, respectively. All parameters with $p < 0.05$.

sea trees planted. Wood density (*WD*) is commonly used in mixed-species biomass models (e.g., Chave et al., 2005; Basuki et al., 2009; Chave et al., 2014; Huy et al., 2019). However, as *WD* reflects the differences in biomass accumulation among species, it may not be a critical predictor for the species-specific biomass models.

The biomass and carbon in branches (*Bbr/Cbr*), leaves (*Ble/Cle*), and bark (*Bba/Cba*) of the tree have greater variation than the biomass and carbon in the stem (*Bst/Cst*) and total (*AGB/AGC*). When the models for estimating *AGC* and its carbon components were developed separately, the errors in the selected models for stem carbon (*Cst*) and total (*AGC*) were the smallest with MAPE = 19.6-20.1% (Table 4). Meanwhile, the errors of the selected branches and leaves carbon models were much higher, with MAPE = 29.8-33.9% (Table 4). On the other hand, with the chosen simultaneous modeling system, the errors in the models of stem carbon (*Cst*), and total (*AGC*) were the smallest, with MAPE = 15.0-16.2% (Table S2), and the errors in the models of branches, leaves, and bark carbon were much higher, MAPE = 25.1-34.8% (Table S2). This may be because of the high variability in the stand density (Table 1) of the agroforestry model studied here. As the density is low, branches and foliage grow stronger and wider, so there are large variations in *Bbr/Cbr* and *Ble/Cle*, making these fitted models have larger errors than other models like *Bst/Cst* and *AGB/AGC.*

Independent vs. simultaneous model fit

Simultaneous modeling systems fit by WNSUR reduced MAPE by 1.3% - 3.9% of *AGB* and *AGC* estimates compared to independent models fit by WNLS (Table 7). This result is consistent with Huy et al. (2019) and Trautenmüller et al. (2021). As expected, the sum of the biomass of the components predicted with independently fit component models differed from the estimates obtained from the *AGB/AGC* models. Using non-additive independent biomass models of tree components and total *AGB* produces biologically inconsistent estimates that scale up to a large area, which affects the final total biomass estimated. Simultaneous fitting leads to higher efficiency than independent fitting because the variance and covariance information of the tree biomass- carbon components and total are included in the model (Parresol, 2001; Poudel & Temesgen, 2016; Trautenmüller et al., 2021).

Table 6. Model equations and estimated parameters for a sole predictor of the diameter at breast height (D) for the simultaneous estimation of AGB/AGC and its components using the WNSUR method (based on the entire dataset).

Prediction of tree *AGB* or *AGC* and its components	Parameters	Estimate ± Std. Error	RMSE (kg tree^{-1})	Adj. R^2
***AGB* and its components**				
$Bst = a_1 \times D^{b1}$	a_1	0.04884 ± 0.01690	0.351	0.935
	b_1	2.27942 ± 0.18910		
$Bbr = a_2 \times D^{b2}$	a_2	0.05699 ± 0.02530	0.175	0.863
	b_2	1.64333 ± 0.24450		
$Ble = a_3 \times D^{b3}$	a_3	0.11233 ± 0.04200	0.240	0.772
	b_3	1.34080 ± 0.20790		
$Bba = a_4 \times D^{b4}$	a_4	0.02612 ± 0.01230	0.178	0.827
	b_4	1.96718 ± 0.26420		
$AGB = Bst + Bbr + Ble + Bba$			0.729	0.916
***AGC* and its components**				
$Cst = a_1 \times D^{b1}$	a_1	0.02224 ± 0.00540	0.165	0.935
	b_1	2.29456 ± 0.13520		
$Cbr = a_2 \times D^{b2}$	a_2	0.02892 ± 0.01330	0.086	0.853
	b_2	1.59982 ± 0.25500		
$Cle = a_3 \times D^{b3}$	a_3	0.04956 ± 0.01770	0.113	0.782
	b_3	1.38225 ± 0.20110		
$Cba = a_4 \times D^{b4}$	a_4	0.01286 ± 0.00613	0.081	0.826
	b_4	1.91162 ± 0.26470		
$AGC = Cst + Cbr + Cle + Cba$			0.352	0.923

Bst/Cst, Bbr/Cbr, Ble/Cle, Bba/Cba, and *AGB/AGC* are biomass/carbon of stem, branches, leaves, bark, and total aboveground biomass/carbon, respectively. All parameters with $p < 0.05$.

Given the above observations along with Fig. 7, a procedure using a simultaneous and weighted modeling system fit by WNSUR is recommended to generate native tree biomass-carbon models and their components. This recommendation is consistent with the comments of Huy et al. (2019) and Trautenmüller et al. (2021).

Carbon sequestration in agroforestry model

The agroforestry model aims to create economic, social, and ecological efficiency. The design and implementation of an agroforestry model that balances economic and environmental factors is always the primary concern, but is not easy to study. Using the selected modeling systems fit by WNSUR to simultaneously predict the biomass-carbon sequestration of *L. glutinosa* including *Bba, AGB* and *AGC* associated with different densities of *Nplant* and *Nstem* to calculate total stem bark biomass ha^{-1}, total *AGB* ha^{-1}, total *AGC* ha^{-1} and total CO_2 equivalent absorbed ha^{-1} for each agroforestry model.

As a result, a popular agroforestry model with a density of 1633 *Nplant* and 1960 *Nstem* of *L. glutinosa*, uses 65% of the space and the remaining 35% of the space to grow cassava until the end of the 6-7 year rotation cycle of *L. glutinosa,* the most valuable component of *L. glutinosa* is the stem bark biomass, which reached 4.7 tons ha^{-1} and the total *AGB*, total *AGC,* and total CO_2 equivalent accumulation reached 15.0 tons ha^{-1} (2.5 tons ha^{-1} year^{-1}), 7.1 tons ha^{-1} (1.2 tons ha^{-1} year^{-1}) and 26.0 tons ha^{-1} (4.3 tons ha^{-1} year^{-1}), respectively. In Austrian mountain agroecosystems, carbon is sequestered in perennial biomass by up to 3.1 tons ha^{-1} year^{-1} (Bertsch-Hoermann et al., 2021), the potential of agroforestry systems in tropical India to accumulate carbon is estimated at 0.3-15.2 tons ha^{-1} year^{-1} (Dhyani et al., 2020). In comparison, the carbon accumulation in the agroforestry model studied here is lower than that of the agroforestry systems in Europe and averages in the Asian region.

Most of the published models have been used to predict tree biomass and apply the default CF of IPCC (2006) for plants is 0.47 to carbon conversion. The CF of the stem bark observed in this study was slightly lower (CF = 0.46),

Table 7. Comparison of Leave-One-Out cross-validation (LOOCV) statistics between two methods of independent weighted non-linear least squares (WNLS) and simultaneous weighted nonlinear SUR (WNSUR) to fit selected AGB and AGC models.

Prediction of tree *AGB* or *AGC*	Method to fit the model	Selected model form	Bias (%)	RMSE (kg tree^{-1})	MAPE (%)
AGB	Independent WNLS	$AGB = a \times (D^2H)^b$	1.8	0.589	20.1
	Simultaneous WNSUR	$AGB = Bst + Bbr + Ble + Bba = a_1 \times D^{b1} + a_2 \times D^{b2} + a_3 \times D^{b3} + a_4 \times (D^2H)^{b4}$	2.2	0.564	18.8
AGC	Independent WNLS	$AGC = a \times (D^2H)^b$	0.9	0.292	20.1
	Simultaneous WNSUR	$AGC = Cst + Cbr + Cle + Cba = a_1 \times (D^2H)^{b1} + a_2 \times D^{b2} + a_3 \times (D^2H)^{b3} + a_4 \times (D^2H)^{b4}$	15.5	0.455	16.2

Bst/Cst, Bbr/Cbr, Ble/Cle, Bba/Cba and *AGB/AGC* are biomass/carbon of stem, branches, leaves, bark and total aboveground biomass/carbon, respectively.

but the CF of the total and other components was higher (CF = 0.48 for branches and total; CF=0.49 for leaves) (Fig. 6). Comparison with this result showed differences in CF among tree parts, therefore, using the same default CF = 0.47 for all parts of the tree could result in a significant error in the conversion. Therefore, the selected modeling system in this study will provide greater confidence in predicting the tree component carbon sequestration than using the tree biomass models and the IPCC's CF.

Conclusions

The leave-one-out cross-validation results showed that the simultaneous WNSUR modeling systems of four tree components and total biomass and carbon of *L. glutinosa* provide better results than fitting independent weighted nonlinear models.

The selected simultaneous modeling systems for biomass and carbon were Eqs. (22) and (27), respectively. In the popular agroforestry model with 65% *L. glutinosa* to 35% cassava mixture, *L. glutinosa* trees reached stem bark biomass (the most valuable component) at 4.7 tons ha^{-1} and CO_2 accumulation at 26.0 tons ha^{-1} at the end of the 6-7-year rotation cycle.

A much larger sample would be necessary to obtain compatible and additive equations using the methodology proposed in this work, which would improve the existing models in terms of the range of applications and robustness of estimates.

Authors' contributions

Conceptualization: B. Huy.
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Funding acquisition: B. Huy.
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Project administration: B. Huy, N. Q. Khiem.
Resources: Not applicable.
Software: Not applicable.
Supervision: H. Temesgen.
Validation: H. Temesgen, K. P. Poudel
Visualization: Not applicable.
Writing – original draft: B. Huy, N. Q. Khiem, N. Q. Truong.
Writing – review & editing: H. Temesgen, K. P. Poudel, B. Huy.

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