NUSANTARA BIOSCIENCE
Vol. 17, No. 2, pp. 203-217
November 2025

ISSN: 2087-3948
E-ISSN: 2087-3956
DOI: 10.13057/nusbiosci/n170218

Destructive sampling-based allometric equations for biomass and carbon estimation in *Acacia* hybrid plantations in Southeastern Vietnam

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Manuscript received: 26 September 2024. Revision accepted: 18 August 2025.

Abstract. *Ha NT, Bao TQ, Tuan NT, Rodríguez-Hernández DI, Dung NT, Ngoan TT. 2025. Destructive sampling-based allometric equations for biomass and carbon estimation in* Acacia *hybrid plantations in Southeastern Vietnam. Nusantara Bioscience 16: 203-217.* This study developed accurate allometric equations for estimating aboveground and belowground biomass, as well as carbon stocks, for *Acacia* hybrid (*Acacia mangium* × *Acacia auriculiformis*) plantations in Southeastern, Vietnam. A dataset of 45 destructively sampled trees with varying ages and diameter classes was used to validate the models. The fresh biomass of the four tree components (stem, branches, leaves, and roots) was measured for a total of 180 samples. Samples were oven-dried at 105°C for stems and branches, and 80°C for leaves, to determine their biomass. Linear and non-linear equations were employed to model both individual tree and stand-level dry biomass (AGB: aboveground biomass, BGB: belowground biomass, TGBG: total biomass), and carbon stocks (AGC: aboveground carbon, BGC: belowground carbon, TGC: total carbon). Diameter at breast height (DBH), tree height (H), stand density (SD), and stand age (A) were included as predictor variables. The best-fitting models were selected based on coefficients of determination (R^2), sum of squared errors (SEE), mean absolute error (MAE), sum of squared residuals (SSR), correction factors (CF), mean absolute percentage error (MAPE), and root mean square error (RMSE), with R^2 values greater than 0.895 and RMSE values less than 0.363. The results revealed strong relationships between aboveground and belowground biomass, and logarithmic functions of DBH and tree height were found to be good predictors for all biomass components. The key equations are: $\ln(AGB) = -3.03805 + 0.586847*\ln(DBH*H) + 1.58329*\ln(DBH)$; $\ln(BGB) = -0.597955 + 0.485409*\ln(DBH)^2$; $\ln(TGB) = -2.65453 + 2.11674*\ln(DBH) + 0.57522*\ln(H)$. Among the variables, DBH was found to be particularly effective in estimating BGB. At the stand level, total biomass (TSB) has a significant correlation with stand density, mean diameter, and stand height, as shown in the following equation: $Ln(TSB) = -9.85561 + 1.09128*\ln(SD) + 1.96789*\ln(D_s) + 0.608831*\ln(H_s)$. These models provide foresters with valuable tools for estimating biomass and carbon accumulation in *Acacia* hybrid plantations. The total carbon stock of the *Acacia* hybrid population in the study area ranged from 29.0 tons/ha to 313.3 tons/ha. This information can support carbon accounting efforts and contribute to Vietnam's initiatives for carbon reduction and climate change mitigation.

Keywords: *Acacia mangium* × *auriculiformis*, allometric modeling**,** carbon stock, destructive sampling, Southeast Asia reforestation

INTRODUCTION

Forest ecosystem plays a large part in mitigating climate change through the sequestration of atmospheric carbon dioxide (CO) and acting as immense carbon sinks under initiatives such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation) (Rizvi et al. 2015; Pham et al. 2019). Tropical rainforests are vital, containing about 25% of the carbon in terrestrial biomass and soils and generating about 34% of the global terrestrial primary production (Dixon et al. 1994). Carbon storage capacity varies tremendously with forest type, site quality, and species (Siraj and Teshome 2017; Tuan et al. 2022). Accurate estimation of aboveground biomass (AGB), belowground biomass (BGB), and overall carbon stocks is therefore essential to comprehending and managing forest carbon cycles (Magerl et al. 2019; Anderson-Teixeira et al. 2021).

Since the 1970s, endeavors like the International Biological Program (IBP) and national forest inventories have encouraged biomass and carbon quantification (Brown and FAO 1997). The first studies by Brown and Lugo (1982) estimated that tropical forests hold 46% of the terrestrial ecosystem carbon, 11% of which is stored in soils. Subsequent studies have estimated biomass in the United States (Jenkins et al. 2003), Australia (NFI 2003), China (Liu et al. 2016; Luo et al. 2020), and other forests (Huy et al. 2016; Salunkhe et al. 2018). Plantation forests are also under the limelight for their relatively high biomass accretion rates, and studies have been carried out on the likes of *Eucalyptus* (Prabha et al. 2023), *Hevea brasiliensis* (Dabi et al. 2021), and *Rhizophora* in Vietnam (Phan et al. 2019; Vinh et al. 2019). Forests around the world hold an estimated 296.2 billion tons of carbon, with the most being stored in South America, followed by Africa, then Europe and Asia (FAO 2015).

Estimation methods of biomass are generally destructive or non-destructive. Destructive methods, involving felling and weighing the trees, are accurate but costly, time-consuming, and disturbance-causing for the environment. Non-destructive methods like allometric models and remote sensing are cost-saving and convenient for large-scale applications (Salunkhe et al. 2018; Schettini et al. 2022). Allometric models relating the diameter, height, and wood density of the tree to biomass are particularly helpful in carbon storage estimation at various scales (Chave et al. 2014).

Studies on *Acacia mangium* and *Acacia auriculiformis* in Bangladesh, Malaysia, Japan, and China have given valuable biomass information (Adam and Jusoh 2018; Zhang et al. 2018). Nevertheless, studies on *Acacia* hybrids (*Acacia mangium* × *Acacia auriculiformis*) in Vietnamese conditions are few. Models tend to use DBH or DBH and height only and ignore variables such as stand density, age, and wood density, which can significantly improve accuracy (Chave et al. 2014; Paul et al. 2016).

Vietnam has about 14 million hectares of forest cover, accounting for 42% of its land area. Plantation forests occupy 4.7 million hectares, with 2.35 million hectares of *Acacia* hybrids dominating more than half of the plantation forest (MARD, 2020). These *Acacia* hybrid plantations are highly valued for rapid growth, short rotation cycles, high productivity, and high carbon sequestration potential (Dinh Kha and Huy Thinh 2017; Adam and Jusoh 2018). They also play an essential role in Vietnam's climate change response, notably achieving the net-zero emission target by 2050 (MONRE 2022). Participation in UN-REDD and the establishment of Measurement, Reporting, and Verification (MRV) systems require region- and species-specific biomass models. However, most apply Tier 1 default values or generic simplified equations that may not be site-specific (IPCC 2006; Pham et al. 2019).

There are over 2,000 hectares of *Acacia* hybrid plantation owned by La Nga Forestry Company in Southeastern Vietnam, yet no localized allometric models exist. Current models (e.g., Bao and Phuc 2018) fail to include site-specific variables, reducing accuracy and practicability.

The research addresses these gaps by developing site-specific allometric models to predict AGB, BGB, and total carbon stores of *Acacia* hybrids in Southeastern Vietnam. Models are developed at the tree and stand levels, incorporating key structural and ecological characteristics. The outcome is expected to enhance forest carbon accounting, aid climate-related forestry policy, and improve global schemes such as REDD+ that promote sustainable forest management and carbon offset schemes.

MATERIALS AND METHODS

Study site and species

The research was conducted at La Nga Forestry Company, Dinh Quan District, Dong Nai Province, Southeastern Vietnam (Figure 1). The area covers about 14,658.55 ha of planted forest, with the geographical coordinates ranging from 11° to 11° 23' latitude and 107° to 107° 22' longitude. The area experiences a subequatorial tropical monsoon climate, with an average annual temperature of 25°C, average rainfall of 3,293 mm, and average annual humidity of 83%. It is located in the transitional zone from the South Central Highlands to the plains. It consists of undulating hills with a maximum elevation of 272 m and a minimum of 60 m. The soil types at the company are grey basalt (16%), red basalt (13%), reddish-yellow ferralitic developed on schist (62%), and alluvial (9%). In 2020, the planted forest in the study site was 14,658.55 hectares, and approximately 2,071 hectares with plantations of *Acacia* hybrid, ranging in age from 1 to 10 years old (MARD 2020).

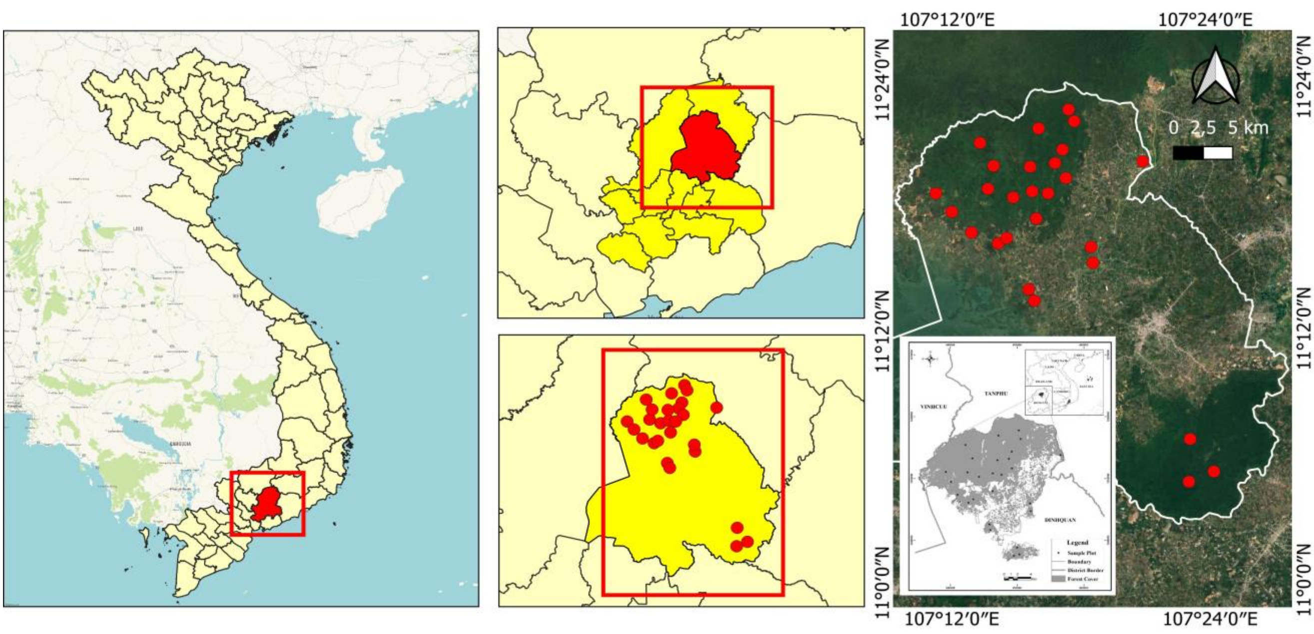

Figure 1. Geographic location of the study area and the sample plots (black stars) where trees of *Acacia* hybrid were harvested

Tree sampling

Tree sampling for *Acacia* hybrid individuals was carried out in forest plantations between 2 and 10 years old, respectively. In this study, we employed the destructive method by felling down trees of different diameters and stand age classes. Specifically, 45 healthy individuals, with diameters at breast height (DBH) ranging from 4 to 22 cm (ages 2 to 10 years), were destructively sampled. The number of sampled trees was stratified by age, with a minimum of three trees per age class. Consequently, the number of trees sampled at each age ranged from three trees (age 8) to six trees (ages 3, 4, 5, and 10) (Table S1). The DBH of each tree was calculated from the measured stem circumference using a diameter tape, with an accuracy of ±1.0 cm. Tree height was measured using a Criterion RD 1000 hypsometer, with a precision of ±0.1 m. These trees were weighed and measured to calculate their fresh biomass for four components: leaves, branches, stems, and roots (Figure 2).

Figure 2. Tree harvesting and destructive sampling showing the separation of each tree component: A. Leaves, B. Branches, C. Stems, and D. Roots with stumps

In total, 180 samples were collected from the 45 trees, with each tree providing four samples (leaves, branches, stems, and roots). Belowground biomass (BGB) was assessed by excavating and weighing coarse roots (>2 mm in diameter). Fine roots (<2 mm) were excluded from sampling due to difficulties in separation and measurement, particularly under field conditions. Root, stem, and branch samples weighed approximately 0.5 to 1.0 kg, while leaf samples weighed between 0.2 and 0.5 kg. The samples were then transported to the laboratory and oven-dried for at least 72 hours at 105°C for stems, branches, and roots, and at 80°C for leaves (Brown and FAO 1997; Chave et al. 2014). After drying, the samples were reweighed to determine the dry to fresh biomass ratio, which was used to calculate the dry biomass for each plant part. Carbon content was analyzed using a TOC/TN analyzer (HT 1300) on a total of 36 dry biomass samples, with 4 samples from each age group at the laboratory of the Southern Academy of Forest Sciences.

Above- and belowground biomass and carbon estimation

In this study, we utilized 20 candidate models to estimate the biomass or carbon content of individual trees and stands (Table S2). The dependent variable (Y) is the biomass or carbon of individual trees or stands, while the independent variables (X) include two key tree dimensions: diameter at breast height (DBH, cm) and tree height (H, m), and two stand characteristics: stand density (SD) and stand age (A). Including tree dimensions (DBH, H) together with stand-level factors (SD, A) provides a comprehensive approach for estimating biomass and carbon stocks, enhancing the accuracy and reliability of forest carbon quantification. In order to evaluate the performance of developed H-DBH models, the data were randomly divided into a training dataset (80%) and a validation dataset (20%). The analysis process was performed using R software (version 4.2.2) with the support of library packages such as Metrics, dplyr, ggplot2, and readxl.

To address potential multicollinearity, we have included a correlation matrix and calculated the variance inflation factor (VIF) for all predictor variables. Variables with VIF values greater than 10 were excluded to reduce multicollinearity and enhance model robustness. Finally, we used several criteria to select the most appropriate models for estimating individual tree and stand biomass, as outlined below:

Coefficient of determination (R^2): In general, the function is considered optimal when R^2 is higher for at least 50%. However, there are cases where the highest R^2 does not correspond to the most suitable model, so it is necessary to rely on other statistical criteria described below.

Verification of model and model parameters: It is required that both the model and its parameters are statistically significant ($p < 0.05$).

Sum of Squares Error (SEE), Mean Absolute Error (MAE), and Sum of Squared Residuals (SSR): The equation is considered best when these three indices are minimized.

Correction Factors (CF): Referencing works by Cao and Li (2019).

$$CF = \exp(RSE^2 / 2) \quad (1)$$

Where: RSE denotes the residual standard error. The model is considered optimal when the Correction Factor (CF) approaches 1.

Mean Absolute Percentage Error (MAPE): This metric is used to test the applicability of the equations and evaluate the level of deviation and average fluctuation of the estimated values produced by the model compared to actual observations.

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \frac{|Yo - Ye|}{Yo} \quad (2)$$

Where: Y_e: predicted observations, Y_o: actual observations; n: the number of observations.

AIC (Akaike information criteria) and BIC (Bayesian Information Criterion):

$$AIC = -n \cdot \ln(RMSE^2) + 2p \quad (3)$$

$$BIC = -n \cdot \ln(RMSE^2) + p * \ln(n) \quad (4)$$

Where: n: the number of observations, p: number of model parameters to be estimated, RMSE: Root mean square error.

Models with a higher coefficient of determination (R^2), and lower values for SSR, SEE, MAE, MAPE, RMSE, and CF, along with statistically significant parameters ($p<0.05$), were selected as the best-fitting biomass allometric equations, fit statistics of non-linear regression analysis also including AIC (Akaike information criteria), and BIC (Bayesian Information Criterion). Information criteria are important measures for selecting non-linear models because they provide a quantitative measure of how well a particular model fts the data. These criteria allow for the selection of the most appropriate non-linear model. Therefore, this study deployed these criteria for further validation of the selected model. The lower ft statistic values indicate a better-ft model.

Additionally, to assess the influence of individual observations on model performance, we calculated Cook's distance and leverage values for all regression models. Observations with a Cook's distance greater than 1.0 were considered potentially influential, and high-leverage points were identified based on the standard leverage threshold $2p/n$, where p is the number of predictors and n is the number of observations (Baba et al. 2021).

RESULTS AND DISCUSSION

Allometric equations for estimating the biomass and carbon stocks of individual tree

Biomass equations for individual tree

Based on 20 candidate models, we developed 12 of the most effective allometric equations for estimating aboveground biomass (AGB), belowground biomass (BGB), and total ground biomass (TGB). All these equations were modeled as a function of diameter at breast height (DBH), tree height (H), age (A), and stand densities (SD). Models with a higher coefficient of determination (R^2), and lower values for SSR, SEE, MAE, MAPE, RMSE, AIC, BIC and CF, along with statistically significant parameters ($p<0.05$), were selected as the best-fitting biomass allometric equations. The selected models are highlighted in bold (Table 1, Table S3).

The results of the correlation analysis and statistical indices indicate that the equations are all statistically significant and have high coefficients of determination (R^2>0.96), with uniform coefficients of determination within allowable limits. This demonstrates a very close relationship between the factors considered. For the AGB estimation model, Model (4), which is a two-dimensional logarithmic model with two factors, has the highest R^2 (0.99). It also has a relatively small estimated standard error, mean absolute error, and correction factor (CF). The RMSE, AIC, BIC for Model (4) is the smallest (Figure 3), and all equation parameters are significant ($p<0.001$). Therefore, Model (4) is suitable for estimating aboveground biomass for individual trees of *Acacia* hybrid.

For the BGB estimation model, the results in Table 1, Figure 3, and Table S3 indicate that all four models exhibit high R^2 coefficients, ranging from 0.886 to 0.901. In addition, the SEE, MAE, AIC, BIC and SSR errors are all minimal. Notably, Model (6) demonstrates the smallest AIC, BIC for test dataset. Consequently, Model (6) was selected for the estimation of BGB for individual *Acacia* hybrids.

Similarly, the results in Table 1, Figure 3, and Table S3 show that the relationship between the total biomass of *Acacia* hybrid individuals and the investigated factors is very close, with a high coefficient of determination (ranging from 0.780 to 0.988). The SSR, SEE, and MAE errors were also all very small, indicating an adequate model fit. Among the models, Model (12) has the highest level of R^2 (0.988 for train dataset and 0.974 for test dataset) and the lowest of AIC and BIC.

Figure 4 shows the correlation and residual error between the observed values and estimated values from the model. The residual error measures how much each observed value deviates from the model built using all observed data. In the error case shown in Figure 4, most of the residuals are less than 0.5, with only a few estimated residuals larger than 0.5 but not exceeding 1.

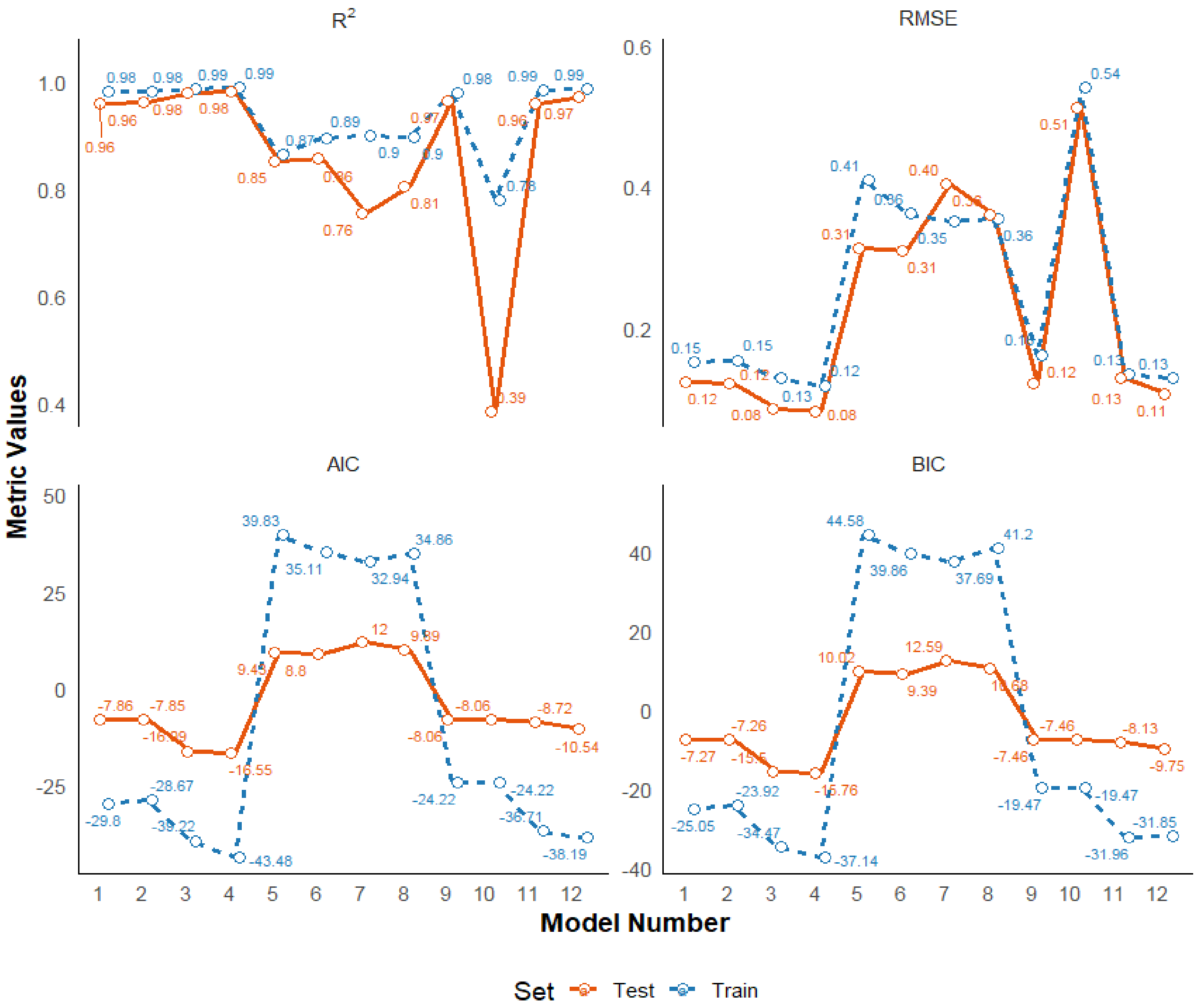

Figure 3. Goodness-of-fit statistics of the most effective models for estimating biomass at the individual tree level. The statistic values are shown for both training and testing datasets

Table 1. The most effective models for estimating individual tree biomass

Component	No.	Allometric equations	Model parameters		
			a	b	c
AGB	1	AGB= exp(a + b*ln(DBH))	-2.42702**	2.56912**	
	2	$\ln(AGB) = (a + b*\ln(\ln(DBH)))^2$	0.540346**	1.59586**	
	3	$\ln(AGB) = a + b*\ln(DBH^2*H)$	-3.37784**	0.952494**	
	4	ln(AGB) = a + b*ln(DBH*H) + c*ln(DBH)	-3.03805***	0.586847***	1.58329***
BGB	5	$BGB = (a + b*DBH^2)^2$	1.44278*	0.0126791**	
	6	$\ln(BGB) = a + b*\ln(DBH)^2$	-0.597955***	0.485409***	
	7	$\log(BGB) = a+ b*\log(DBH^2*H)$	-4.15561**	0.862991**	
	8	log(BGB) = a + b*log(DBH*H) + c*log(DBH)	-3.70196**	0.37481***	1.70517**
TGB	9	TGB = exp(a+ b*ln(DBH))	-2.0556*	2.50782**	
	10	ln(TGB) = exp(a + b*ln(DBH))	-0.0188452*	1.57559*	
	11	$\ln(TGB) = a + b*\ln(DBH^2*H)$	-2.98404**	0.929806**	
	12	ln(TGB) = a+ b*ln(DBH) + c*ln(H)	-2.65453***	2.11674***	0.57522***

Note: Regression models are more suitable for biomass prediction and are printed in bold, AGB: Aboveground dry biomass, BGB: Belowground dry biomass, DBH: Diameter at breast height, H: Tree height, TGB: Total dry biomass. *significant at $P<0.05$; **significant at $P<0.005$ level; ***significant at $P<0.001$ level

Carbon equations for individual tree

Developing a carbon estimation model contributes to carbon storage monitoring and quantifying the environmental value of forests. Carbon estimation models with high coefficient of determination and small errors are summarized and presented in Table 2 and Table S4.

The analysis of the correlation and model error of terrestrial carbon estimates reveals a strong connection between terrestrial carbon stocks and the investigated factors. The coefficient of determination is notably high (ranging from 97.5% to 99.0%), and the model parameters are statistically significant, with coefficients of variation and errors within acceptable limits. Model (15) shows the smallest error compared to MAPE (MAPE=9.62%), while model (14) has the largest MAPE (15.38%). Consequently, model (15) is deemed suitable for estimating aboveground carbon for *Acacia* hybrid (refer to Table 2, Figure 5 and Table S4).

Similarly, testing various functions with statistical criteria to select optimal variables and functions for estimating underground carbon shows that underground biomass carbon has a strong relationship with diameter at breast height. As shown in Table 2, Figure 5 and Table S4, the coefficients of determination of the four models are all relatively high (>86.6%). Models (17) and (18) exhibit the highest MAPE, at 36.13% and 28.09%, respectively. However, Model (20) has the highest coefficient of determination (0.901) and the lowest value of RMSE, AIC and BIC, at 0.352, 32.94, and 37.69, respectively. Therefore, Model (20) is suitable for estimating belowground carbon for *Acacia* hybrid trees.

Since the components of a tree (stem, branches, bark, leaves, roots) are closely related, biomass and carbon for components that are difficult to measure directly below ground can be estimated from models with different predictor variables (Kenzo et al. 2020; Handavu et al. 2021; Annighöfer et al. 2022), or from the relationship between aboveground and belowground biomass carbon (Bieluczyk et al. 2023). Therefore, equation (20) enables the rapid estimation of belowground carbon based on tree growth variables, such as diameter at breast height.

Carbon sequestration is now a recognized forest management mechanism, supported by economic mechanisms at the macro level, primarily due to the "Carbon Credits" initiative. Developing a forest tree carbon estimation model is thus valuable for forest management planning and calculating energy reserves in forest biomass. The error and correlation analysis of the models (Table 2, Figure 5 and Table S4) indicates that the coefficients of determination are very high (97.36% to 98.71%), demonstrating a strong relationship between total tree carbon and the investigation factors D and H. Additionally, the errors are small and within permissible limits. Model (23) records the highest coefficient of determination (98.8%) and the smallest error compared to MAPE (9.77%). Model (22) has the highest MAPE value (15.04%) and the lowest coefficient of determination (96.50%). Hence, model (23) is suitable for estimating the carbon of *Acacia* hybrid.

Figure 6 illustrates the correlation and residual error between observed values and estimated carbon values from the model. Similar to the biomass estimation model, the residual error is assessed to compare each observed value against the model built using all observed data. Most residuals are less than 2, with only a few estimated residuals exceeding 2 but not surpassing 5.

Allometric equations for estimating the biomass plantations

By testing various types of functions that relate biomass to investigation factors and basic growth of the forest stand, we explored single-variable functions, multi-variable functions, and combinations of variables to select the most optimal model for estimating biomass in a population. The variables tested in these functions included: Stand diameter (Ds), stand height (Hs), stand age (A) and stand density (SD).

The results of constructing a biomass estimation model for an *Acacia* hybrid forest stand are summarized in Table 3. The results of error analysis and the correlation between biomass and investigated factors in an *Acacia* hybrid forest stand show that the coefficients of determination of the models are very high, ranging from 94.12% to 99.31%

(Table 3). This demonstrates a close relationship between forest biomass and the investigated factors such as DBH, H, N, and A. The models and their parameters are all significant at a 99% confidence level. Additionally, the errors (SSR, SEE, MAE) are small. Model (28) has the highest coefficient of determination (>99%) and the smallest error compared to MAPE (4.99%) (refer to Table 3, and Figure 7). Hence, model (28) is the most suitable for estimating the total biomass of *Acacia* hybrid forests.

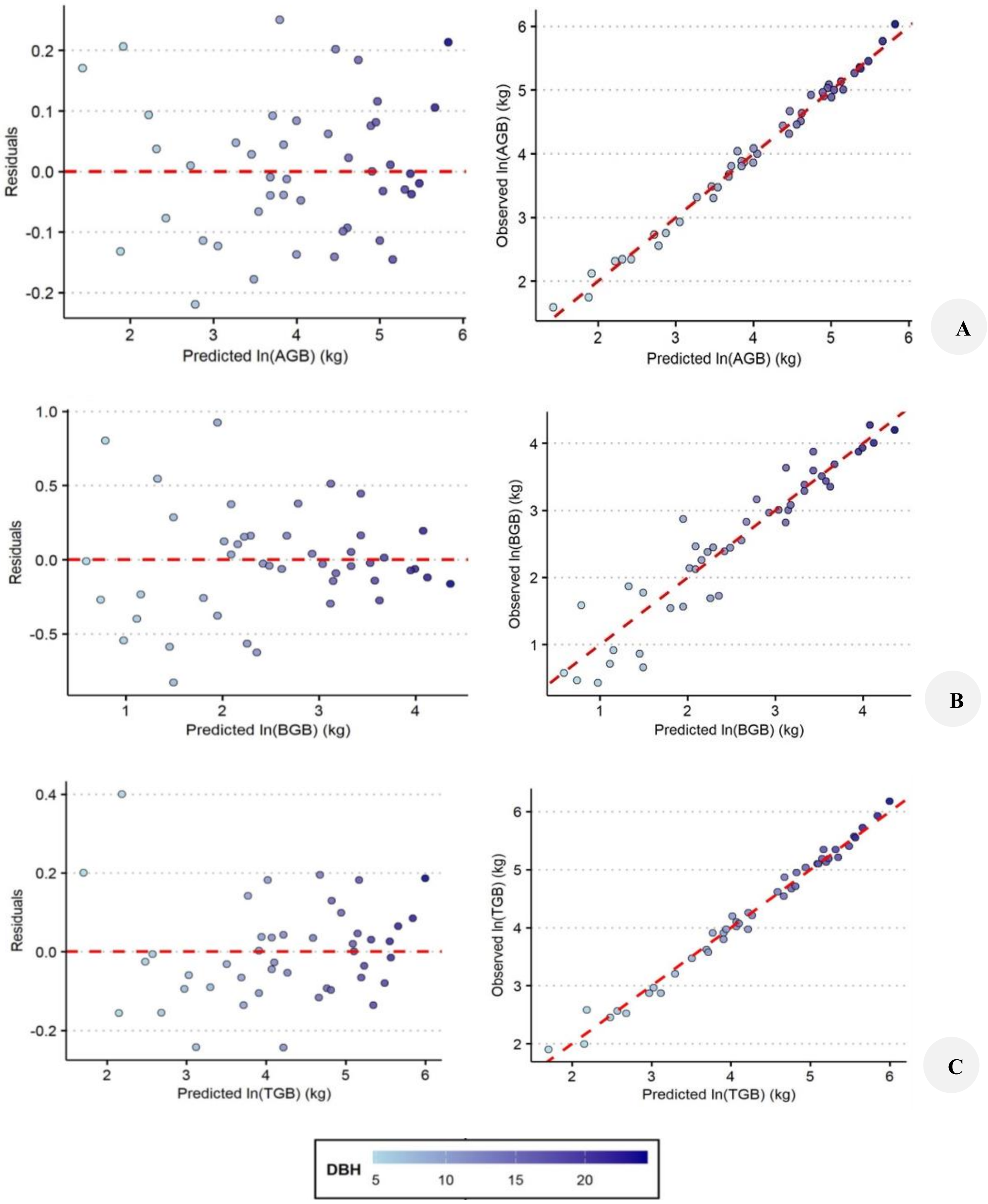

Figure 4. Scatter plots illustrating the comparison between individual tree biomass of *Acacia* hybrid obtained from field measurements and our estimation method. A. Aboveground dry biomass, B. Belowground dry biomass, C. Total dry biomass

Table 2. The most effective models for estimating carbon stocks of *Acacia* hybrid individual tree

Component	No	Allometric equations	Model parameters		
			a	b	c
AGC	13	AGC = exp(a + b*ln(DBH))	--3.14061**	2.56921**	
	14	AGC = exp(a+ b*sqrt(DBH))	-2.0804**	1.50233*	
	15	ln(AGC) = a+b *ln(DBH) + c*ln(H)	-3.75174***	2.17016***	0.586943**
	16	ln(AGC) = a+ b*ln(DBH^2*H)	-4.09147	0.952527	
BGC	17	BGC = (a + b* $DBH^2)^2$	1.00944***	0.00887663***	
	18	BGC = (a+ b* $DBH)^2$	-0.504757**	0.250682*	
	19	ln(BGC) = a+ b*ln(DBH) +c*ln(H)	-4.42019**	2.08145**	0.375082*
	20	ln(BGC) = a+ b*ln(DBH^2*H)	-4.87416*	0.863603**	
TGC	21	TGC = exp(a+ b*ln(DBH))	-2.76832**	2.50757**	
	22	TGC = (a+ b* $DBH)^2$	-1.55574*	0.614246*	
	23	ln(TGC) = a+ b*ln(DBH) + c*ln(H)	-3.36645**	2.11701***	0.574454***
	24	ln(TGC) = a+ b*ln(DBH^2*H)	-3.69657**	0.929702**	

Note: regression models are more suitable for biomass prediction, are printed in bold, AGC: Aboveground carbon, BGC: Belowground carbon, DBH: Diameter at breast height, H: Tree height, TGC: Total carbon, *significant at P<0.05; **significant at P<0.005 level; ***significant at P<0.001 level

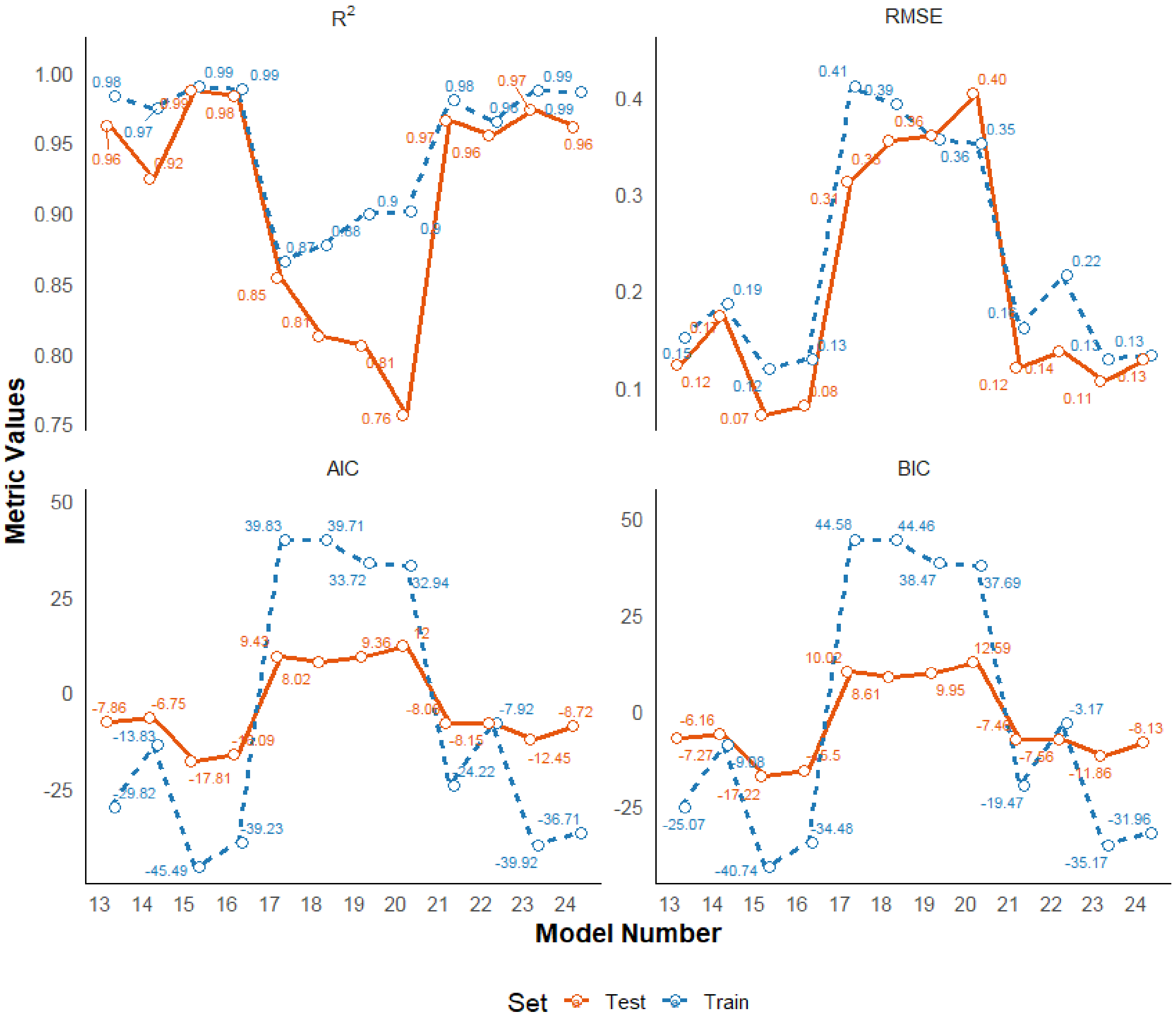

Figure 5. Goodness-of-fit statistics of the most effective models for estimating carbon at the individual tree level. The statistic values are shown for both training and testing datasets

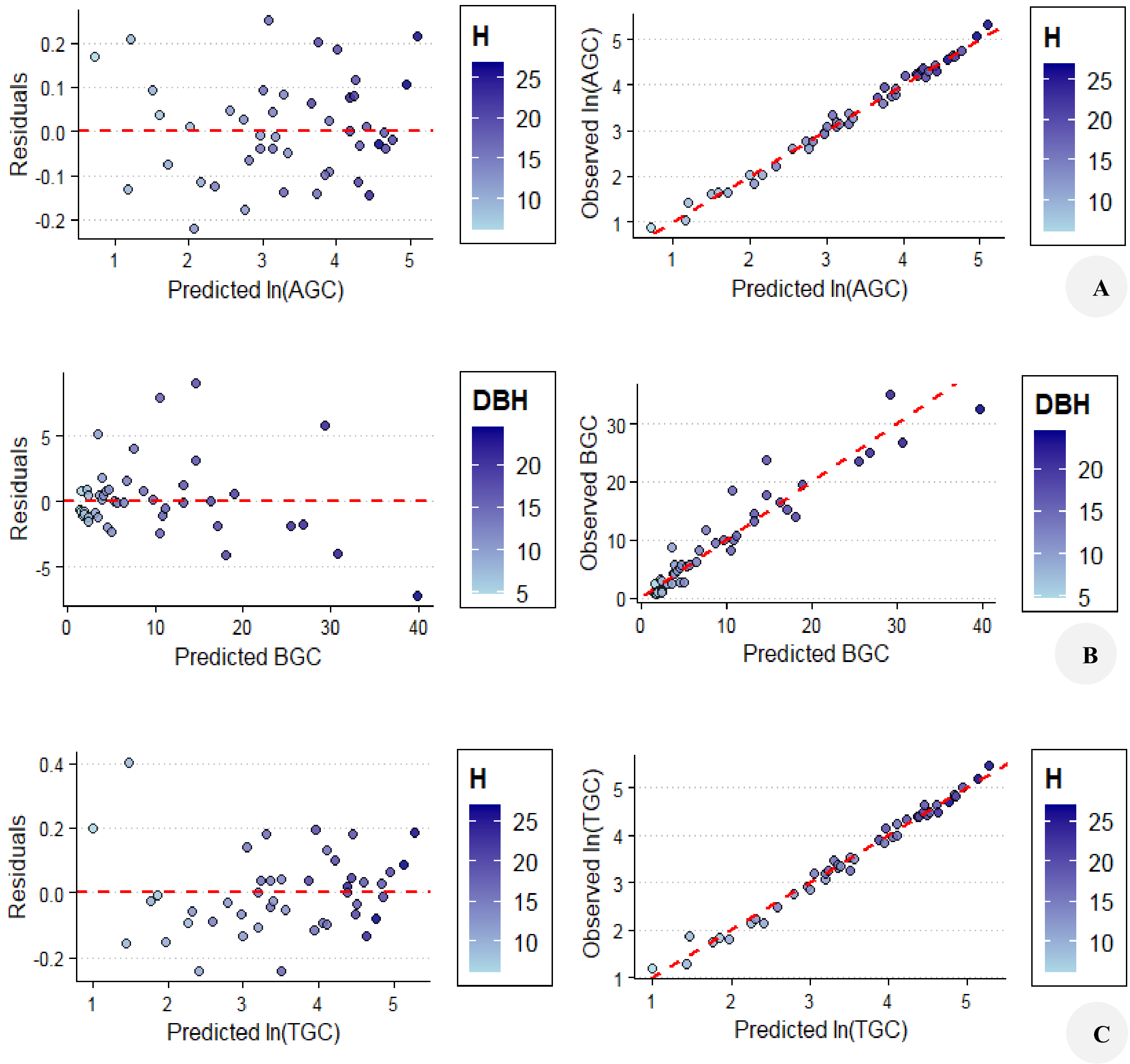

Figure 6. Correlation and bias of the *Acacia* hybrid carbon estimation model. A. Aboveground carbon, B. Belowground dry carbon, C. Total dry carbon. Note: All carbon values are expressed in kg

Table 3. Models for estimating total stand BGB of *Acacia* hybrid plantations

No.	Allometric equations	Model evaluation statistics					
		R^2	SSR	SEE	MAE	MAPE	CF
25	$Ln(TSB) = -10.8046 + 1.21052*ln(SD) + 2.65308*ln(D_s)$	98.89	0.22	0.08	0.06	6.01	1.00
26	$Ln(TSB) = -11.3581 + 1.48312*ln(SD* D_s) + 0.836347*ln(A)$	94.12	1.15	0.18	0.14	12.72	1.02
27	$Ln(TSB) = -9.94382 + 0.22143*ln(A) + 2.33323*ln(D_s) + 1.14724*ln(SD)$	99.29	0.14	0.06	0.05	5.05	1.00
28	$Ln(TSB) = -9.85561 + 1.09128*ln(SD) + 1.96789*ln(D_s) + 0.608831*ln(H_s)$	99.31	0.14	0.06	0.05	4.99	1.00

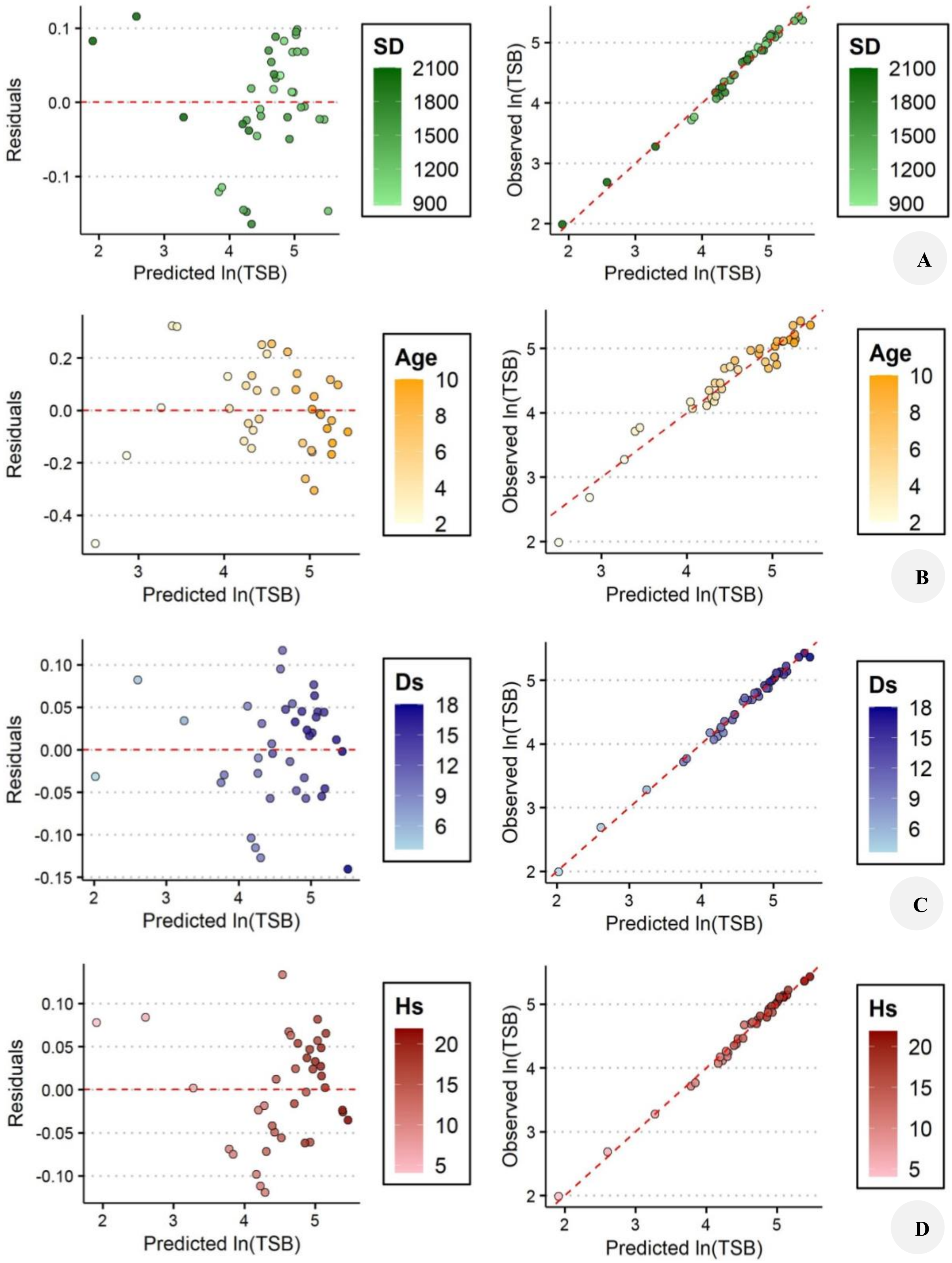

Figure 7. Comparison of four logarithmic regression models for estimating the stand biomass of *Acacia* hybrid (TSB). A. Model 25, B. Model 26, C. Model 27, D. Model 28. TGB: the stand biomass of *Acacia* hybrid (ton/ha), D_s: Stand diameter (cm), Hs: Stand height (m), A: Stand age (years), SD: stand density (trees/ha)

Discussion

First, using allometric equations to estimate forest biomass and carbon stocks is a highly accurate and reliable method, and it has been repeatedly applied worldwide (Chave et al. 2014; Paul et al. 2016; Doan et al. 2025). Second, this study employs a combination of exponential and log-linear functions to estimate biomass and carbon. Many domestic and international studies have found that these, along with linear functions, are common functional forms for biomass estimation (Anitha et al. 2015; Bao and Phuc 2018; Brahma et al. 2021; Cabrera-Ariza et al. 2021).

The criteria for selecting the best-fit model for each biomass component included R^2, Mean Absolute Error (MAE), Correction Factor (CF), Sum of Squared Residuals (SSR), and mean absolute percentage error (MAPE). While most studies rely on the R^2 coefficient for function selection, some incorporate MAE and SRR criteria as well (Anitha et al. 2015; Huy et al. 2016; Paul et al. 2016; Nguyenthi 2017; Bao and Phuc 2018). Additionally, some studies consider Correction Factor (CF) and Sum of Squared Errors (SEE) (Bao and Phuc 2018; Altanzagas et al. 2019; Levan et al. 2020) and Mean Absolute Percentage Error (MAPE) (Nguyenthi 2017; Tashi et al. 2017; Pothong et al. 2022). These criteria are widely used for selecting suitable functions to estimate forest biomass and carbon accumulation.

Regarding the variables used to estimate biomass and carbon, the biomass and carbon equation refers to the relationship between the biomass and carbon of a tree (or its parts such as trunk, branches, leaves, roots) with one or more investigation variables (such as diameter, height, wood weight, density) (Luo et al. 2020; Aneseyee et al. 2021; Cabrera-Ariza et al. 2021). This study estimates the biomass and carbon of individual *Acacia* hybrid trees using an equation that includes either diameter or height, or both D and H. For estimating biomass and carbon of *Acacia* hybrid plantations, many variables such as D, H, N, A, and combinations of D and H, D, H, and N were used. The results show that models estimating total biomass and carbon can use variables such as diameter, height, density, and age. Specifically, *Acacia* hybrid biomass and carbon have a closer relationship with the two factors D and H than with just D. Additionally, the research indicates that using more variables such as density, diameter, and height yields, more accurate results than using a single variable.

A synthesis of 5,924 forest biomass estimation equations in China shows that 43.5% of the equations are based on a single predictor (diameter or height), while 56.5% are based on two predictors (diameter and height) or a combination of both. Among these, diameter at breast height is the most commonly used variable in biomass equations (96.8%) (Luo et al. 2020). The use of the diameter variable in biomass equations is also common in Europe, India, Indonesia, and Africa, with 46%, 48%, 55%, and 63%, respectively (Anitha et al. 2015; Brahma et al. 2021). This preference is due to the ease of measuring diameter in practice and its suitability for estimating forest biomass and carbon (Anitha et al. 2015).

In general, many research projects on biomass and carbon have been conducted using various methods, with the commonly used method based on the correlation equation between biomass and investigated criteria of standard trees or plantations. Some authors confirm that tree biomass and carbon depend closely on tree trunk diameter, thus building a correlation function with diameter at breast height (Solomon et al. 2017; Adam and Jusoh 2018; Aneseyee et al. 2021). However, other authors assert that biomass and carbon also depend on tree height, thereby using both diameter and height for better estimation results (Huy et al. 2016; Abich et al. 2019).

According to Altanzagas et al. (2019), tree biomass and carbon can be estimated from predictor variables such as diameter, height, and wood density. The above results show that forest tree biomass and carbon have a close relationship with the investigated factors D, H, N, and A. Therefore, biomass and carbon can be estimated from the variables D, or a combination of D and H, or a combination of D, H, and N. This approach is consistent with the scientific and practical basis of many national and international studies conducted on woody plants, trees, and shrubs in plantations (Huy et al. 2016; Nguyenthi 2017; Abich et al. 2019; Altanzagas et al. 2019; Handavu et al. 2021; Bieluczyk et al. 2023).

This study will be used to inform the development and deployment of climate mitigation programs, including REDD+, the Clean Development Mechanism (CDM), and voluntary offset markets. *Acacia* hybrid stands and other forest plantations have become more trusted components of national greenhouse gas (GHG) inventories and carbon sequestration activities in Vietnam (Pham et al. 2019). The allometric models developed here provide convenient methods for predicting aboveground and belowground biomass with more precision, which is required to calculate carbon credits and monitor changes over time. The result of this study also supports Tier 2 methods under IPCC guidelines by being regionally calibrated models, reducing uncertainty less than default emission factors (IPCC 2006). Besides, these models can also be integrated into project-level Monitoring, Reporting, and Verification (MRV) systems, satisfying Vietnam's updated Nationally Determined Contributions (NDCs) and forest-based climate solution commitment (MONRE 2022). With the growth of the voluntary carbon market in Southeast Asia, especially with interest in nature-based solutions, solid biomass equations such as here will be essential for enabling scientifically valid and financially viable forest carbon projects (Hamrick and Gallant 2017).

In conclusion, we developed 10 suitable allometric equations to accurately estimate the biomass and carbon stocks of individual trees and plantations of *Acacia* hybrid in Southeastern Vietnam. Among these, the linear logarithmic function with two factors DBH and tree height was the most appropriate for estimating the total biomass and total carbon stocks of *Acacia* hybrids. Additionally, a single-factor linear function with independent DBH as predictor variable was suitable for estimating total biomass and BGB of *Acacia* hybrid. The study also demonstrated the relationship between AGB and BGB using a correlation function, with the predictor variable being biomass or AGC. Whereas the biomass and carbon for the *Acacia* hybrid at stand-level were estimated using a linear logarithmic model with three predictor variables: DBH, H, and stem density, in the form: Ln(TSB) = -9.85561 + 1.09128*ln(SD) + 1.96789*ln(Ds) + 0.608831*ln(Hs). With these findings, foresters charged with managing this forest type can now implement these models to more accurately estimate the biomass and carbon accumulation over time of *Acacia* hybrid in a more accurate way. To apply these models in practice, users need to measure one or more of the following variables in the field such as DBH, H. Once these parameters are recorded, users can substitute the measured values into the corresponding biomass or carbon equation (e.g., for aboveground biomass, belowground biomass, or total biomass) provided in this study. The output will yield an estimate of dry biomass (kg) or carbon stock (kg/tree) for each individual tree. This study emerges as the foundation for accurately calculating the total fresh biomass and carbon stocks of *Acacia* hybrid forests in Southeastern Vietnam and benefits the country to meet its carbon reduction goals. However, this study also has limitations. Although the allometric models demonstrated high predictive power within the sample plantations managed by La Nga Forestry Company in Southeastern Vietnam, caution should be exercised when applying them to other regions. Additionally, moisture content may vary across seasons and tree ages, especially in leaf tissues, potentially affecting the accuracy of dry biomass estimation despite the use of oven-drying protocols. Variability in *Acacia* clone types, soil characteristics, climate, and silvicultural practices may affect tree allometry and model accuracy. Therefore, we recommend local model calibration and/or the inclusion of site-specific random effects before broader application. Further studies should validate and refine these models across diverse ecological zones to enhance their applicability.

ACKNOWLEDGEMENTS

We would like to thank La Nga Forestry Company Limited, Vietnam, for generously granting permission to conduct this study. The authors would also like to thank our colleagues and the staff of La Nga Forestry Company Limited for their support in data collection. Additionally, we express our appreciation to the editorial team and the anonymous reviewers for their valuable comments and suggestions.

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Table S1. Number of destructively sampled trees

No.	Age (years)	DBH (cm)	H (m)
1	2	4.77	6.2
2	2	5.25	9.5
3	2	6.53	10.7
4	2	6.68	8.1
5	2	7.8	9.2
6	3	6.05	10
7	3	7.96	11
8	3	9.24	12.5
9	3	9.87	13.5
10	3	12.42	14.5
11	3	10.19	12.5
12	4	7.32	12.8
13	4	9.87	15.5
14	4	10.51	15.7
15	4	15.92	16.7
16	4	11.3	12
17	4	12.1	13
18	5	5.41	9
19	5	10.51	16.5
20	5	11.15	16.6
21	5	17.2	20.4
22	5	13.1	13
23	5	16.07	15.8
24	6	11.46	15
25	6	21.66	19
26	6	14.8	16.5
27	6	15.44	16.8
28	7	7.96	15
29	7	13.38	21
30	7	17.83	21
31	7	17.83	20
32	7	18.78	18.4
33	8	9.87	17
34	8	14.01	20.6
35	8	19.42	19
36	9	10.83	17
37	9	16.24	24.5
38	9	22.61	27
39	9	21.33	20.7
40	10	11.78	17.6
41	10	17.2	22
42	10	18.47	24
43	10	19.11	27
44	10	26.43	29
45	10	22.28	20.7

Table S2. Models are used to estimate the biomass and carbon of individual trees or plantations

No.	Equations
1	$Y = (a + b.x)^2$
2	$Y = 1/(a + b/x)$
3	$Y = a + b.\log x$
4	$Y = a + b.x^2$
5	$Y = a + b.x + c.x^2$
6	$Y = a + b.x.z$
7	$Y = a + b.x.z^2$
8	$Y = a + b.x^2.z$
9	$Y = a + b.x + c.x^2.z$
10	$Y = a + b.z + c.x^2.z$
11	$Y = (a + b.\mathrm{sqrt}(x))^2$
12	$Y = \mathrm{sqrt}(a + b.x^2)$
13	$Y = \exp(a + b.x)$
14	$Y = a.x^b$
15	$Y = a.\exp(-b.x^{-c})$
16	$\log Y = a + b.\log x + c.\log z$
17	$\log Y = a + b.\log(x.z)$
18	$\log Y = a + b.\log(x^2.z)$
19	$\log Y = a + b.\log(x.z^2)$
20	$\log Y = a + b.\log x + c.\log(x.z)$

Table S3. Goodness-of-fit statistics of the most effective models for estimating biomass at the individual tree level

Train dataset									
Model	**R2**	**SSR**	**SEE**	**MAE**	**MAPE**	**CF**	**RMSE**	**AIC**	**BIC**
Model 1	0.984	0.822	0.155	0.125	12.191	1.011	0.151	-29.800	-25.050
Model 2	0.983	0.857	0.159	0.125	12.152	1.012	0.154	-28.670	-23.920
Model 3	0.988	0.600	0.133	0.108	10.911	1.008	0.129	-39.220	-34.470
Model 4	0.990	0.504	0.122	0.099	9.860	1.007	0.118	-43.480	-37.140
Model 5	0.866	6.061	0.422	0.308	36.149	1.088	0.410	39.830	44.580
Model 6	0.895	4.745	0.374	0.269	27.896	1.068	0.363	35.110	39.860
Model 7	0.901	4.459	0.362	0.259	26.914	1.064	0.352	32.940	37.690
Model 8	0.899	4.557	0.366	0.255	26.424	1.065	0.356	34.860	41.200
Model 9	0.980	0.945	0.167	0.131	12.846	1.013	0.162	-24.220	-19.470
Model 10	0.780	10.507	0.556	0.457	38.076	1.157	0.540	-24.220	-19.470
Model 11	0.987	0.645	0.138	0.104	10.282	1.009	0.134	-36.710	-31.960
Model 12	0.988	0.597	0.132	0.100	9.761	1.008	0.129	-38.190	-31.850
Test dataset									
	R2	**SSR**	**SEE**	**MAE**	**MAPE**	**CF**	**RMSE**	**AIC**	**BIC**
Model 1	0.962	0.138	0.141	0.103	10.534	1.008	0.124	-7.860	-7.270
Model 2	0.964	0.130	0.136	0.096	9.833	1.007	0.120	-7.850	-7.260
Model 3	0.982	0.065	0.096	0.064	6.690	1.004	0.085	-16.090	-15.500
Model 4	0.983	0.061	0.093	0.067	6.984	1.003	0.082	-16.550	-15.760
Model 5	0.854	0.880	0.355	0.226	24.633	1.050	0.313	9.430	10.020
Model 6	0.857	0.859	0.350	0.230	25.429	1.049	0.309	8.800	9.390
Model 7	0.756	1.467	0.458	0.298	35.401	1.085	0.404	12.000	12.590
Model 8	0.806	1.170	0.409	0.260	30.774	1.067	0.361	9.890	10.680
Model 9	0.966	0.131	0.137	0.108	11.157	1.007	0.121	-8.060	-7.460
Model 10	0.387	2.371	0.582	0.440	33.259	1.141	0.513	-8.060	-7.460
Model 11	0.961	0.151	0.147	0.102	10.670	1.008	0.130	-8.720	-8.130
Model 12	0.974	0.101	0.120	0.082	8.550	1.006	0.106	-10.540	-9.750

Table S4. Goodness-of-fit statistics of the most effective models for estimating carbon at the individual tree level

Train dataset									
Model	**R2**	**SSR**	**SSE**	**MAE**	**MAPE**	**CF**	**RMSE**	**AIC**	**BIC**
Model 13	0.984	0.821	0.155	0.125	12.184	1.011	0.151	-29.820	-25.070
Model 14	0.975	1.261	0.193	0.147	14.323	1.018	0.187	-13.830	-9.080
Model 15	0.990	0.516	0.123	0.098	9.623	1.007	0.120	-45.490	-40.740
Model 16	0.988	0.603	0.133	0.110	11.031	1.008	0.129	-39.230	-34.480
Model 17	0.866	6.057	0.422	0.308	36.130	1.088	0.410	39.830	44.580
Model 18	0.877	5.548	0.404	0.277	28.086	1.080	0.393	39.710	44.460
Model 19	0.899	4.557	0.366	0.255	26.389	1.065	0.356	33.720	38.470
Model 20	0.901	4.459	0.362	0.259	26.885	1.064	0.352	32.940	37.690
Model 21	0.980	0.945	0.167	0.131	12.847	1.013	0.162	-24.220	-19.470
Model 22	0.965	1.688	0.223	0.160	15.038	1.024	0.217	-7.920	-3.170
Model 23	0.988	0.597	0.133	0.100	9.767	1.008	0.129	-39.920	-35.170
Model 24	0.987	0.645	0.138	0.104	10.286	1.009	0.134	-36.710	-31.960
Test dataset									
Model	**R2**	**SSR**	**SSE**	**MAE**	**MAPE**	**CF**	**RMSE**	**AIC**	**BIC**
Model 13	0.962	0.138	0.141	0.103	10.539	1.008	0.124	-7.860	-7.270
Model 14	0.925	0.271	0.197	0.151	15.380	1.015	0.174	-6.750	-6.160
Model 15	0.987	0.047	0.082	0.059	6.116	1.003	0.072	-17.810	-17.220
Model 16	0.983	0.060	0.093	0.062	6.399	1.003	0.082	-16.090	-15.500
Model 17	0.854	0.879	0.354	0.226	24.624	1.050	0.313	9.430	10.020
Model 18	0.812	1.129	0.402	0.253	31.087	1.065	0.354	8.020	8.610
Model 19	0.806	1.169	0.409	0.260	30.746	1.067	0.360	9.360	9.950
Model 20	0.757	1.465	0.458	0.298	35.366	1.085	0.404	12.000	12.590
Model 21	0.966	0.131	0.137	0.108	11.154	1.007	0.121	-8.060	-7.460
Model 22	0.956	0.171	0.157	0.115	12.351	1.010	0.138	-8.150	-7.560
Model 23	0.974	0.101	0.120	0.082	8.551	1.006	0.106	-12.450	-11.860
Model 24	0.961	0.151	0.147	0.102	10.672	1.008	0.130	-8.720	-8.130