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ORIGINAL ARTICLE

Aboveground biomass models for *Acacia mangium* Willd. growing at the eastern plains of Colombia

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Abstract

Accurate biomass models are important tools for estimating biomass and carbon sequestration in forest plantations. Thirty *Acacia mangium* trees, aged 13 years, were destructively sampled to determine the distribution of aboveground biomass (AGB) in the main tree components. Six allometric models using diameter at breast height (DBH), total height (H) and crown diameter (CD) as independent variables were fitted using weighted nonlinear regression and evaluated through Monte Carlo cross-validation. *Acacia mangium* trees primarily accumulate biomass in the stem (51.2 - 58.0 %) and branches (24.6 - 31.5 %), and these proportions tend to remain stable across tree sizes. All tree-level variables showed positive correlations with AGB; however, the strongest correlations were observed with DBH and CD. The developed models displayed slightly better predictive accuracy compared to existing ones. These models will contribute to improving the carbon quantification of *Acacia mangium* forest plantations in the eastern plains of Colombia.

Keywords: carbon quantification, climate change mitigation, afforestation, reforestation.

1. INTRODUCTION

Greenhouse gas emissions, mainly CO_2, have increased since the middle of the 20th century (IPCC, 2007), giving rise to growing concern about climate change and its mitigation strategies (Traoré et al., 2018). One of the main strategies for climate change mitigation is carbon sequestration by forests because forests can store large amounts of carbon (Cuong et al., 2020).

Forest plantations cover 294 million hectares worldwide, which is equivalent to approximately 7 % of the global forest area (FAO, 2022) and supply around 46.3 % of the world's wood consumption (Payn et al., 2015). Additionally, forest plantations are considered effective tools to counteract climate change due to their capacity for carbon sequestration, playing an increasingly important role in climate regulation (Cuong et al., 2020).

Consequently, it is crucial to develop studies that improve the estimates of carbon stocks in forest plantations and enhance the long-term productivity of these production systems. This will help reduce atmospheric CO_2 levels by enhancing carbon sequestration in tree tissues.

Following the recommendations of the IPCC (2007), it is essential to have tools for the quantification of biomass and carbon sequestration, adopting an appropriate level (Tier) to predict carbon capture and storage. A Tier represents a level of methodological complexity. According to the IPCC (2019) there are usually three tiers provided. Tier 1 is the basic method, Tier 2 is intermediate, and Tier 3 is the most demanding in terms of complexity and data requirements (IPCC, 2019). Tier 2 requires the development of local (or regional) biomass models for quantifying carbon stocks and fixation rates in forest plantations.

Allometric models are commonly used to predict tree biomass by describing empirical relationships among tree variables. A simple allometric model is analytically represented as a power functions because it assumes that a plant maintains the proportions between different parts over time throughout its development (Douterlungne et al., 2013; Picard et al., 2015). Biomass models relate the aboveground (or belowground) biomass of the tree with easily measured predictor tree-level variables such as diameter (Picard et al., 2012). However, some authors have shown that including other tree-level predictor variables such as total height, crown diameter, and wood density can contribute to enhancing prediction accuracy (Huynh et al., 2022).

Acacia mangium Willd. is a fast-growing tree species native to Australia, Papua New Guinea, and Indonesia (Kachaka et al., 2021). It has been widely cultivated on a large scale in Tropical America, Southeast Asia, and many African countries (Koutika & Richardson, 2019), mainly due to its fast growth, drought tolerance, adaptation to different soil types, and the good wood quality it offers for the production of solid products, boards, and energy (Reyes et al., 2018; Kachaka et al., 2021).

In Colombia, *Acacia mangium* was introduced in the early 1990s and is currently the most cultivated species in the country, with 67,581 ha located mainly in the region known as the eastern plains (MADR, 2023). This species has been successfully used in the recovery of soils degraded by mining (Torres & Del Valle, 2007), silvopastoral agroforestry systems (Giraldo et al., 2006), and pure forest plantations (Espitia et al., 2010). Torres & Del Valle (2007) reported volumes of 231,374 m^3 ha^{-1} at an age of 9.55 years (~24.23 m^3 ha^{-1} yr^{-1}) for the species growing in the savannas of the Caribbean region on fertile but eroded and compacted soils due to extensive livestock use.

Its rapid growth and adaptability make it an attractive species for climate change mitigation through carbon sequestration in land use, land use change, and forestry (LULUCF) projects (IPCC, 2007). These initiatives can greatly contribute to fulfilling Colombia's commitments established in the Nationally Determined Contribution (NDC) under the United Nations Framework Convention on Climate Change (UNFCCC) (Government of Colombia, 2020).

The objective of this study is to quantify and model the aboveground biomass (AGB) of *Acacia mangium* trees growing in forest plantations in the eastern plains of Colombia. The specific objectives are: (i) to quantify the biomass of the components of *Acacia mangium* trees of different sizes; (ii) to determine which tree-level variables improve the accuracy of aboveground biomass predictions using allometric models, and (iii) to select the most appropriate allometric models to predict aboveground biomass of *Acacia mangium* trees growing in forest plantations.

2. MATERIALS AND METHODS

2.1. Study area

The study area is located in the eastern plains of Colombia, on the northwestern side of the Vichada department at coordinates 5°35'00"N and 69°23'08"W (Figure 1). The area is at an altitude of 110 m above sea level. The average annual temperature is 27 °C, and the annual average precipitation is approximately 2359 mm. The precipitation follows a monomodal distribution, with a dry season from December to March and a wet season for the remainder of the year. The driest month is January, with an average precipitation of 15.2 mm, while the highest average precipitation occurs in June and July, with averages of 384 and 387.6 mm, respectively (IDEAM, 2023). The predominant soils in the study area are loam to clay-loam with an acidic pH ranging from 4.8 to 5.9. These soil types are associated with sedimentary mega-basins located between the Guiana Shield and the eastern flank of the Andes (eastern mountain range). The region is characterized by Quaternary deposits of fluvial origin and sedimentary rocks (Romero, 2023).

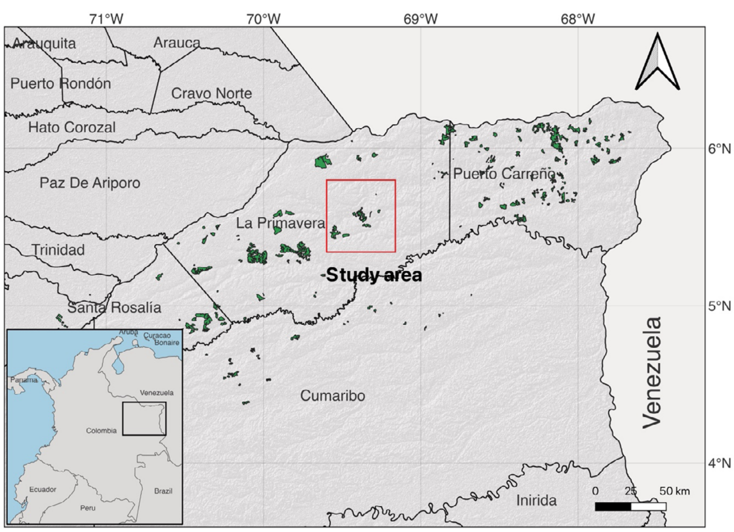

Figure 1. Geographical location of the study area in the eastern plains of Colombia. The green polygons represent forest plantations that have been established.

2.2. Tree selection and destructive sampling

In the study, 30 trees with diameters at 1.3 m (DBH) ranging from 5.5 cm to 24.3 cm and total heights (H) between 4.7 m and 13.9 m were selected from two 13-year-old stands (Table 1). Prior to felling, the DBH was measured using a diameter tape. Crown radii were recorded in the North-South-East-West orientations using a metric tape, and from these measurements, the crown diameter (CD) was calculated. Once the tree was felled, the H was measured using a metric tape. The trees were divided into four components: stem, branches, leaves, and flowers/fruits (Huynh et al., 2021).

The fresh weight of these components was initially determined using digital hook scales immediately after the tree was cut in the field. Following this, three fresh subsamples of each component (branches, leaves, flowers/fruits), each approximately 200 g in weight, were measured in the field using a digital scale with a precision of 0.1 g and placed into plastic bags. Subsequently, 3 cm thick discs were extracted from the stem at heights of 1.3 m, ½, and ¾ of the total tree height, and these discs were weighed in the field using a digital scale with a precision of 0.1 g to obtain the fresh weight. All fresh samples were then stored in plastic bags until they were transported to the laboratory.

In the laboratory, the samples of leaves and flowers/fruits were oven-dried at 60 °C, while the branches were oven-dried at 103 °C until reaching a constant weight. The discs were immersed in water, and the fresh volume with and without bark was determined by water displacement (ASTM, D2395). The proportion of bark was calculated as the volume of bark divided by the total fresh volume of the disc. Subsequently, the discs were oven-dried at 103 °C until reaching a constant weight. The wood basic density (WD) of each disc was determined by dividing the oven-dried weight by the fresh volume of the disc. An average WD for each tree was calculated by averaging the WD of the three discs collected from it. The moisture content (MC) was obtained for each component as the average of the MC of the three subsamples, and this average was then used to calculate the observed biomass of each component using the following equation:

$$B = MC_s \cdot W_{tf} = \left(\frac{W_{sod}}{W_{sf}}\right) \cdot W_{tf} \qquad (1)$$

where B is the biomass of each component, MC_s is the average moisture content of the subsamples, W_{sod} and W_{sf} represent the average oven-dry and fresh weights of the subsamples, respectively, and W_{tf} is the total fresh weight of the component.

2.3. Distribution of biomass by component

The biomass within the stem was divided into solid wood biomass (B_{stem}) and stem bark biomass (B_{bark}). The latter was calculated by multiplying the stem biomass by the proportion of bark. Subsequently, the biomass of all tree components was aggregated to compute the aboveground biomass ($AGB = B_{stem} + B_{bark} + B_{branches} + B_{leaves} + B_{flowers/fruits}$).

As shown in Figure 2, the stem accounted for the largest biomass proportion, averaging 53.7 %, followed by branches (27.6 %), stem bark (11.1 %), leaves (7.3 %), and finally flowers and fruits (0.2 %). While the biomass proportion of bark and leaves showed a slight downward trend with increasing tree size, the biomass proportions of the stem and branches remained relatively constant across different diameter classes. However, the biomass proportion of the stem in the 20-25 cm diameter class exhibited a substantial increase (Figure 2).

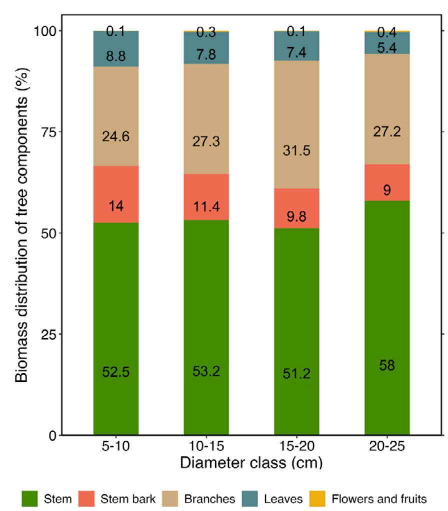

Figure 2. Biomass distribution among tree components of *Acacia mangium* across different diameter classes.

Table 1. Descriptive statistics for the variables of *Acacia mangium* sample trees used to fit the allometric models for aboveground biomass.

Diameter class	n	DBH (cm)				H (m)				CD (m)				WD (g cm⁻³)			
		Mean	Min	Max	CV (%)	Mean	Min	Max	CV (%)	Mean	Min	Max	CV (%)	Mean	Min	Max	CV (%)
5-10	5	7.8	5.5	9.7	26.3	7.4	4.7	9.9	25.7	3.7	2.8	4.1	14.7	0.529	0.332	0.590	21.11
10-15	11	13.0	11.1	15.0	11.3	10.0	7.7	11.3	11.0	4.5	2.9	5.4	16.7	0.550	0.458	0.586	6.95
15-20	9	17.4	15.8	19.1	6.4	10.4	8.9	11.6	9.2	5.7	4.8	7.0	13.1	0.580	0.508	0.619	5.85
20-25	5	21.5	20.3	24.3	7.6	12.7	11.7	13.9	7.0	6.0	5.0	6.8	11.3	0.557	0.493	0.637	9.84
All	30	14.9	5.5	24.3	31.3	10.1	4.7	13.9	19.0	5.0	2.8	7.0	22.1	0.557	0.332	0.637	10.28

2.4. Relationship between AGB and predictor variables

Scatterplots were used to visualize the relationships between tree-level variables and AGB (Figure 3). It is evident that DBH and H show nonlinear relationships, while CD and WD primarily exhibit linear relationships with AGB.

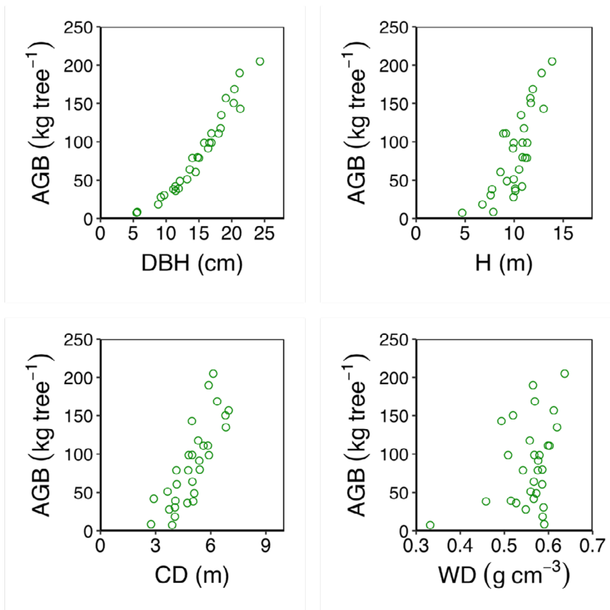

Figure 3. Relationship between AGB and tree-level predictor variables. DBH is diameter at breast height (cm), H is total height (m), CD is crown diameter (m), and WD is wood basic density (g cm^{-3}).

All tree-level variables showed positive Pearson's correlation coefficients, indicating that all variables contribute directly to the increase of AGB (Figure 4). The strongest correlation was observed between AGB and DBH ($r = 0.97$, $p < 0.0001$), followed by CD ($r = 0.81$, $p < 0.0001$), H ($r = 0.79$, $p < 0.0001$) and finally WD ($r = 0.36$, $p = 0.05$). Tree-level variables exhibiting stronger correlations with AGB were selected as candidates for developing predictive models for AGB.

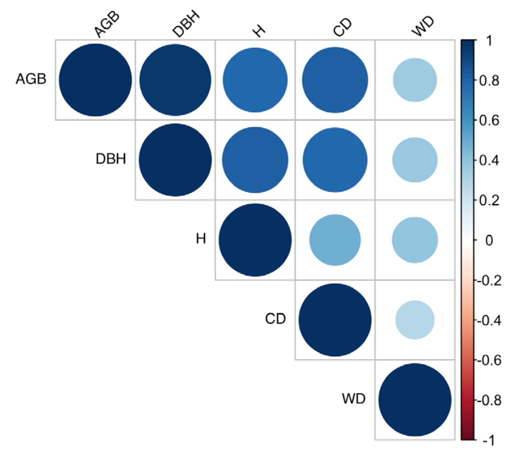

Figure 4. Pearson's correlation coefficient matrix between AGB and predictor variables. DBH is diameter at breast height (cm), H is total height (m), CD is crown diameter (m), and WD is wood basic density (g cm^{-3}).

2.5. Allometric models evaluated

The simplest form of an allometric biomass model, using the power law, includes DBH as a predictor variable due to its ease of measurement in forest inventories (Huynh et al., 2022). Additionally, covariates such as H, and CD, were incorporated into the model, resulting in the models presented in Table 2.

Table 2. Aboveground biomass models evaluated. AGB is the aboveground biomass (kg tree^{-1}), DBH is diameter at breast height (cm), H is total height (m), and CD is crown diameter (m).

Model #	Model form	Weighting variable
1	$AGB_i = \beta_1 \cdot DBH_i^{\beta_2} + \varepsilon_i$	$\frac{1}{DBH_i^{\delta}}$
2	$AGB_i = \beta_1 \cdot DBH_i^{\beta_2} \cdot H_i^{\beta_3} + \varepsilon_i$	$\frac{1}{DBH_i^{\delta}}$
3	$AGB_i = \beta_1 \cdot DBH_i^{\beta_2} \cdot CD_i^{\beta_3} + \varepsilon_i$	$\frac{1}{DBH_i^{\delta}}$
4	$AGB_i = \beta_1 \cdot DBH_i^{\beta_2} \cdot H_i^{\beta_3} \cdot CD_i^{\beta_4} + \varepsilon_i$	$\frac{1}{DBH_i^{\delta}}$
5	$AGB_i = \beta_1 \cdot (DBH_i^2 \cdot H_i)^{\beta_2} + \varepsilon_i$	$\frac{1}{(DBH_i^2 \cdot H_i)^{\delta}}$
6	$AGB_i = \beta_1 \cdot (DBH_i^2 \cdot H_i)^{\beta_2} \cdot CD_i^{\beta_3} + \varepsilon_i$	$\frac{1}{(DBH_i^2 \cdot H_i)^{\delta}}$

Note: β_1, β_2, .., β_k are parameters to be estimated and δ is a parameter to be estimated that determines the shape of the weight function (e.g. $w_i = 1/DBH_i^{\delta}$) .

2.6. Model training and testing

The AGB models were fitted using weighted nonlinear regression with the 'gnls' function, which is part of the 'nlme' package in R (R Core Team, 2023). In this study, a weighting variable (e.g., DBH) was incorporated for each model (Table 2). The varPower function within the 'gnls' function was used to estimate the parameter δ directly from the data during the model fitting process (Pinheiro and Bates, 2000). The effectiveness of the weighting variable was assessed by examining the patterns of the weighted residuals post-model fitting.

Monte Carlo cross-validation (MCCV) was used for model training and testing. MCCV is commonly used to evaluate model performance by repeatedly partitioning the dataset into training and testing subsets, ensuring that the model is assessed on data not used during the fitting process. This resampling technique provides multiple estimates of model performance, reducing variability and enhancing reliability, particularly in scenarios with limited data availability (Xu and Liang, 2001). The procedure used by MCCV involved generating R random resamples without replacement. R should be sufficient to reconstruct the distribution of model parameters. Previous studies have shown that when sample size is small, the number of resamples needs to be large (Xu and Liang, 2001; Shan, 2022). The number of resamples was determined according to Xu and Liang (2001), who suggested that R could be calculated as $R = n^2$. Therefore, a total of $R = 1000$ resamples were considered. In each resample, 80 % of the data were used for training, while the remaining 20 % were used for testing the model. The parameter estimates, goodness of fit, and test statistics represent the averages across the 1000 realizations of each model. The 95 % confidence interval for each parameter was determined as $CI = \bar{\beta}_i \pm 1.96 \cdot Sd_{\beta_i}$ (where, $\bar{\beta}_i$ and Sd_{β_i} are the parameter mean and standard deviation, respectively). Measures of goodness of fit, such as Pseudo-R^2, the corrected Akaike criterion (AICc), and the AICc differences (ΔAICc) were calculated (Burnham & Anderson, 2002). Additionally, test statistics including the mean percentage error (MPE), and the mean absolute percentage error (MAPE) were used (Despotovic et al., 2016; Aliffia & Karnaningroem, 2019).

$$Pseudo - R^2 = \frac{1}{R}\sum_{r=1}^{R}\left(1 - \frac{\sum_{i=1}^{n_{train}}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n_{train}}(y_i - \bar{y})^2}\right) \quad (2)$$

$$AICc = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{2 \cdot n_{train} \cdot k}{n_{train} - k - 1} - 2 \cdot \ln(L)\right) \quad (3)$$

$$MPE = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{100}{n_{test}}\sum_{i=1}^{n_{test}}\frac{(y_i - \hat{y}_i)}{y_i}\right) \quad (4)$$

$$MAPE = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{100}{n_{test}}\sum_{i=1}^{n_{test}}\frac{|y_i - \hat{y}_i|}{y_i}\right) \quad (5)$$

where y_i and $\hat{y}_i$ are the observed and predicted values, respectively, and n_{train} and n_{test} are the sample sizes for training and testing ($n_{train} = 24$ and $n_{test} = 6$, respectively), k is the number of parameters of the model, $\ln(L)$ is the log-likelihood function for the model and R is the number of resamples used in MCCV.

The allometric models exhibiting superior goodness of fit and test statistics were deemed optimal. To further evaluate these models, a graphical analysis was conducted using the 'ggplot2' library (R Core Team, 2023). Diagnostic graphs, depicting observed versus predicted values were generated to assess the predictive accuracy of each model and additionally, graphs of weighted residuals versus predicted values were analyzed to evaluate whether heteroscedasticity was effectively corrected. Comparisons with existing literature models were conducted to evaluate performance and validate predictive accuracy against established benchmarks.

3. RESULTS

3.1. Parameters estimates and goodness of fit

The parameters of all the AGB allometric models, which follow a power law form, were positive, indicating that each variable contributes to an exponential increase in biomass (Table 3). Based on the calculated 95 % confidence intervals, all parameters are statistically significant. All the allometric models demonstrate a high predictive accuracy, accounting for a large proportion of the observed variability in AGB, with Pseudo-R^2 ranging from 0.929 to 0.972. The AICc ranged between 165.0 and 182.4, with the lowest AICc observed for Model 4 and the highest for Model 5. Model 4, boasting the best goodness of fit, integrates all the available independent variables DBH, H, and CD, while Model 5, exhibiting the poorest goodness of fit, solely incorporates the combined variable $DBH^2{\cdot}H$.

Once the model with the lowest AICc (Model 4) was identified, the ΔAICc for each alternative model was computed by subtracting the AICc of Model 4 from the AICc of each alternative model. Based on the ΔAICc, all the models exhibited similar behavior, with small ΔAICc of less than 4.3, except for Model 5, which had a notably higher ΔAICc (ΔAICc = 17.4).

Table 3. Parameter estimates, confidence intervals (in brackets) and goodness of fit and prediction accuracy for allometric AGB models for *Acacia mangium*.

Model #	Parameter estimates and 95 % confidence interval				Goodness of fit			Test statistics	
	β_1	β_2	β_3	β_4	Pseudo-R^2	AICc	ΔAICc	MPE (%)	MAPE (%)
1	0.14777 (0.1245 - 0.1711)	2.31371 (2.2537 - 2.3737)			0.956	167.7	2.7	−1.34	9.46
2	0.12437 (0.0938 - 0.1550)	2.22742 (2.1419 - 2.3130)	0.17590 (0.0232 - 0.3286)		0.954	168.6	3.6	−1.21	9.36
3	0.14320 (0.1040 - 0.1822)	2.13809 (1.9531 - 2.3240)	0.31664 (0.088 - 0.5449)		0.972	166.7	1.7	−1.34	9.96
4	0.09219 (0.0649 - 0.1195)	1.92131 (1.7751 - 2.0675)	0.38006 (0.1990 - 0.5611)	0.40579 (0.2579 - 0.5537)	0.970	165.0	0	−1.10	8.38
5	0.06326 (0.0366 - 0.0899)	0.92140 (0.8597 - 0.9831)			0.929	182.4	17.4	−1.34	9.46
6	0.05591 (0.0370 - 0.0748)	0.80116 (0.7485 - 0.8538)	0.65118 (0.4914 - 0.8110)		0.954	169.3	4.3	−1.21	9.36

3.2. Test statistics of allometric models

Analysis based on MCCV showed that all the models slightly overpredicted AGB, with MPE ranging from −1.1 % to −1.34 % and MAPE between 8.38 % and 9.96 % (Table 3).

Consistent with the training phase, the AGB allometric Model 4 yielded the best results in the testing phase (Table 3), with the lowest MPE = −1.10 %, and MAPE = 8.38 %. However, it is important to note that the improvement in the predictive accuracy between the more complex model (Model 4) and the simpler one (Model 1) is minimal, with differences of only 0.2 % in MPE and 1.1 % in MAPE.

Figure 5 illustrates the relationship between predicted and observed AGB, along with the weighted residuals generated for each model using the average estimated parameters from MCCV. The graph shows that all models consistently predict AGB, closely aligning with the 1:1 diagonal line. However, there is a slight tendency for all models to overpredict AGB for larger trees, which is more pronounced in Model 5 and Model 6, which included the combined variable ($DBH^2 \cdot H$). Nonetheless, it can be observed that the first four models perform better overall, with predictions that are, on average, closer to the observed AGB. Furthermore, the weighted residuals of the models do not show evidence of heteroscedasticity in the graphs.

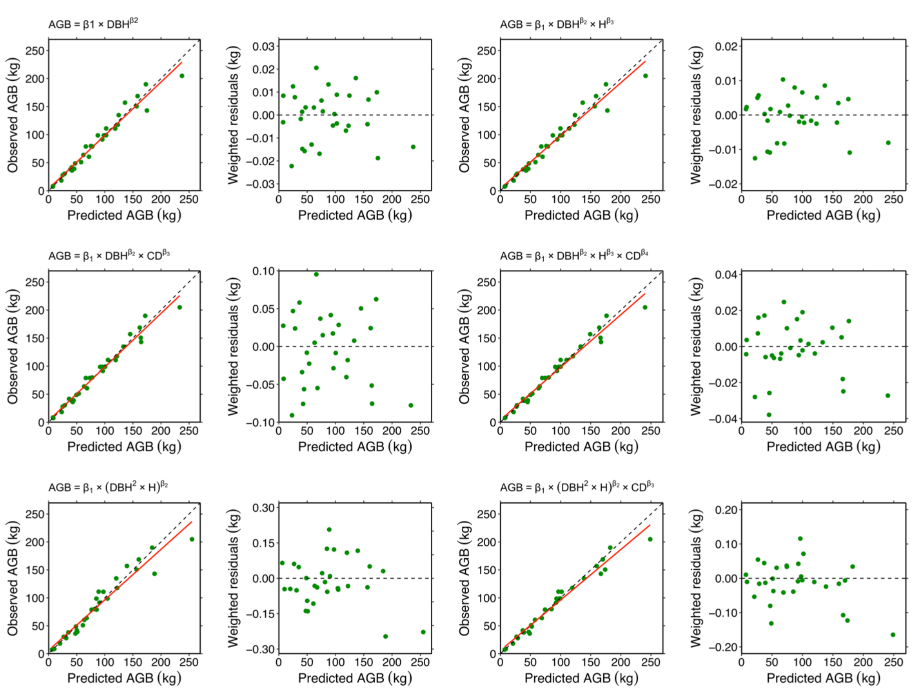

Figure 5. Observed vs predicted AGB and weighted residuals versus predicted AGB for evaluated models using average estimated parameters obtained from MCCV.

A comparison between the models developed in this study (Model 1 and Model 4) and various AGB models previously published for *Acacia mangium* is presented in Figure 6. These include models reported by Adam & Jusoh (2018), Cuong et al. (2020) and Miyakuni et al. (2004) for *Acacia mangium* plantations in Malaysia, Vietnam and Indonesia, respectively, and a model reported by Giraldo et al. (2006) for silvopastoral agroforestry systems in the plains of the Caribbean region of Colombia. It is noteworthy that all the compared models only use DBH as the independent variable.

The observed AGB of our sample trees was compared to the predicted AGB generated by the published models. The assessed models demonstrate relatively accurate predictions up to approximately 16 cm in diameter but tend to overpredict biomass for larger DBHs. The models most closely aligned with Model 1 and Model 4 are those of Giraldo et al. (2006) and Miyakuni et al. (2004).

The compared models underwent testing using the MCCV method with a 20 % random split of the data and 1000 resamples for testing. The same test statistics, such as MPE and MAPE, were calculated. Analysis of test statistics revealed that the model by Giraldo et al. (2006) exhibited the lowest MPE (–0.20 %), followed by Model 1 (–1.57 %), Model 4 (–1.92 %) and the model by Miyakuni et al. (2004) (7.90 %). However, Model 1 and Model 4 demonstrated lower MAPE (8.73 % and 7.08 %) than the other models.

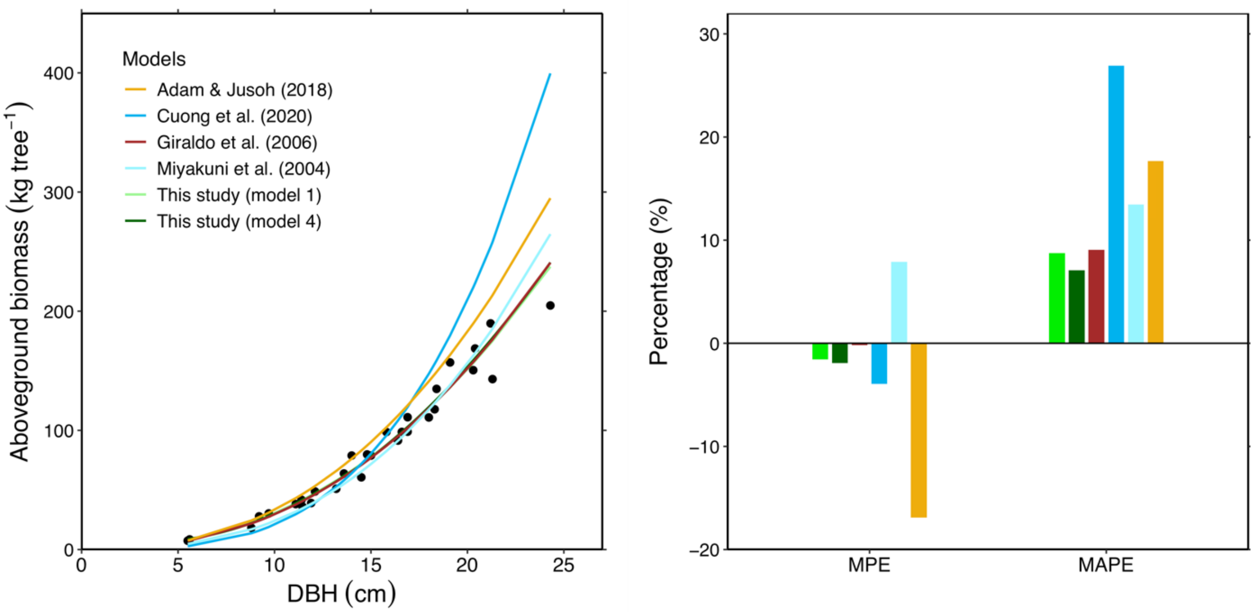

Figure 6. Comparison of the Model 1 and Model 4 of this study and different published models for *Acacia mangium*. Considering that Model 4 includes DBH, H, and CD as independent variables, the predictions of this model were smoothed to fit into the graph (left panel) and facilitate comparison with the other models.

4. DISCUSSION

Acacia mangium trees consistently allocate a substantial proportion of biomass to both the stem and branches across diameter classes. This observation underscores the preservation of allometric patterns regardless of tree sizes (Cuong et al., 2020; Heriansyah et al., 2007; Adam and Jusoh, 2018). These proportions are consistent with those reported by Cuong et al. (2020) for *Acacia mangium* in the Southeastern region of Vietnam but differ from those observed in *Acacia mangium* trees in Côte d'Ivoire (Traoré et al., 2018).

A smaller proportion of biomass is allocated to leaves and flowers and fruits across tree sizes. However, it is important to note that the proportion of biomass in the crown or leaves of a tree may vary depending on phenological stages. For example, deciduous species temporarily lose their leaves during drought episodes or in winter. Additionally, crown biomass proportion can indicate competition levels within a stand, with greater competition leading to smaller crowns (Tonini et al., 2018).

Similar to previous studies, our study confirms that all the evaluated tree-level variables directly contribute to increasing AGB. However, the strongest correlations were observed with DBH and CD. Considering that the stem constitutes the most substantial biomass component in the tree and its volume correlates predominantly with DBH (Burkhart & Tomé, 2012), it is unsurprising that DBH exerts the greatest influence on total AGB. The remaining

AGB is allocated to branches, leaves, flowers and fruits. Consequently, we anticipate a positive correlation between AGB and CD (Huynh et al., 2022).

Fitting allometric biomass and volume models often leads to heteroskedasticity issues (Barrios et al., 2014), where residual variance increases as the predictor variable also increases. In our study, weighted nonlinear regression was used to address heteroscedasticity, assigning appropriate weights to observations based on their variance, which helped minimize the effect of heteroscedasticity in the model fitting process (Pinheiro and Bates, 2000). This approach has been successfully used by Huynh et al. (2022) and Torres & Del Valle (2007) for *Corymbia citriodora* and *Acacia mangium*, respectively, eliminating the need for logarithmic transformations.

MCCV has proven to be an effective technique for model training and testing, known for its capacity to enhance confidence in results and repeatability through averaging over multiple random dataset partitions, thus reducing variance (Xu and Liang, 2001). However, it is worth noting that MCCV tends to introduce higher bias compared to other cross-validation methods such as k-fold cross-validation (Xu and Liang, 2001; Shan, 2022). Notably, Kozak and Kozak (2003) suggested that cross-validation yields model fit statistics estimates similar to those obtained from using the entire dataset, implying that it may not offer additional insights compared to statistics directly derived from models built on complete datasets. Shan (2022) also observed that while MCCV outperforms other techniques for smaller sample sizes, there are no statistical differences between cross-validation techniques for larger sample sizes.

Overall, all the evaluated models exhibited good performance in both fitting and testing phases. However, Model 4 stood out by demonstrating the best goodness of fit and better test statistics. This AGB model incorporated additional variables such as H and CD, alongside DBH. However, the inclusion of these additional tree-level variables alongside DBH, only marginally improved model performance, compared with Model 1, which only includes DBH.

Variables such as H and CD are technically challenging to measure in forest inventories, as they are typically indirect measurements and often carry more uncertainty than DBH. Their measurement is labor-intensive, raising inventory costs (López et al., 2013). However, remote sensing data now enables the derivation of H and CD, aiding AGB prediction (Shi et al., 2024; Xiao et al., 2024). Incorporating these variables, along with DBH, into AGB models is often species-dependent; while some studies support their inclusion to improve model accuracy, others find no significant improvement (Nogueira et al., 2021; Mulatu et al., 2024).

Models incorporating the combined variable ($DBH^2 \cdot H$) generally exhibited lower predictive accuracy. This variable aims to address collinearity between H and DBH (Picard et al., 2015; Dutcă et al., 2019). However, Picard et al. (2015) found minimal improvement compared to models with separate DBH and H variables in African rainforest tree biomass models. Hence, using separate variables is preferable when collinearity is not an issue (Dutcă et al., 2019).

Comparing the models developed in this study with published *Acacia mangium* models in similar latitudes, we found that Cuong et al. (2020) and Adam & Jusoh (2018) models for plantations in Vietnam and Malaysia overpredicted our AGB data. In contrast, the model by Miyakuni et al. (2004), developed for Indonesian plantations, showed strong concordance despite geographic differences. The model by Giraldo et al. (2006) resembled Model 1 and Model 4, suggesting potential generalizability across Colombian regions. Test statistics indicate Model 1 and Model 4 slightly outperform Giraldo et al. (2006) in MAPE with a lower MPE.

Acacia mangium is the most important species for commercial reforestation in Colombia, with considerable potential for expansion in less developed areas, such as the eastern plains. Therefore, specific biomass models for this region are vital for precise carbon sequestration projects. They not only enhance project reliability but also provide insights into forest productivity and carbon storage, crucial for effective climate change mitigation efforts.

5. CONCLUSIONS

This study aimed to quantify and model AGB of *Acacia mangium* trees in forest plantations in the eastern plains of Colombia. We observed consistent biomass allocation to stems and branches across different diameter classes, indicating the maintenance of allometric patterns regardless of tree size. Our analysis confirmed that all evaluated tree-level variables, particularly DBH and CD, directly contribute to increasing AGB. Models including additional variables like CD and H, alongside DBH demonstrated slightly better goodness of fit and predictive accuracy. Our models slightly outperformed previously published models, suggesting potential for broader application across diverse regions of Colombia. These models provide valuable tools for sustainable forest management and climate change mitigation efforts in Colombia, enhancing the Tier level in carbon estimation for such ecosystems and offering practical solutions to improve carbon quantification. The models for *Acacia mangium* in Colombia could be further improved by incorporating additional data from diverse sites, thereby increasing geographical representativeness and improving the precision of model parameter estimates.

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