

Beyond the Breast Height: Leveraging Stump Diameter as a Robust Predictor of Biomass and Carbon Stocks in Tropical Acacia Plantations

Niamjit Das

niamjit.forestry@gmail.com

Shahjalal University of Science and Technology

Md. Qumruzzaman Chowdhury

Shahjalal University of Science and Technology

Research Article

Keywords: Stump diameter, Stem biomass, Acacia auriculiformis, Acacia mangium, Hybrid Acacia, REDD+, Carbon accounting, Sustainable forestry

Posted Date: July 29th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10230871/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Accurate estimation of tree biomass is essential for tropical forest management, climate change mitigation and REDD+ monitoring. While conventional inventories rely on diameter at breast height (DBH), measurement of DBH is often impractical in dense stands, buttressed stems, or post-harvest contexts. This study evaluates stump diameter (*dst*, measured at 30 cm above ground) as a robust proxy for DBH and stem biomass in *Acacia auriculiformis*, *A. mangium*, and their hybrid plantations in Bangladesh. We measured a stratified sample of 1050 trees and destructive sampling of 75 individuals for calibration. Fourteen models (linear, ln–ln, polynomial, mixed-effects, and machine learning) were tested using adjusted R^2 , RMSE, AIC, and Durbin–Watson statistics. The parsimonious ln–ln regression performed very well ($R^2 > 0.98$) and confirmed that stump diameter was a reliable predictor. Biomass models based on stump performed similarly as models based on DBH, whereas mixed effect models reduced the bias particularly for hybrid Acacia. Validation with independent datasets and five-fold cross validation confirmed unbiased predictions ($p > 0.05$) with narrow confidence intervals. Random Forest also validated the major predictor as stump diameter. However, Gradient Boosting showed some over-fitting. The species-specific carbon stock estimates showed that hybrid Acacia was the most productive followed by *A. mangium* and *A. auriculiformis*. This study provides a practical tool for rapid biomass assessment and carbon accounting after harvest. The results contribute to the global climate and biodiversity goals, supporting SDG 13 (Climate Action) and SDG 15 (Life on Land) by allowing effective monitoring, reporting and verification of carbon stocks in tropical plantation forestry.

1 Introduction

Tree biomass estimation underpins forest ecology, sustainable management, and climate change research, providing the basis for carbon accounting and biodiversity assessments. Biomass is a proxy for forest productivity, carbon sequestration and ecosystem services and thus an important parameter for scientific as well as policy purposes [1, 2]. Tropical forests have a disproportionately large role in the global carbon cycle, holding almost a third of the carbon stocks of the terrestrial biosphere [3, 4]. Therefore, accurate biomass estimates are essential for national greenhouse gas inventories, REDD+ programs and sustainable forest management strategies [5, 6].

DBH (diameter at breast height) is a well-established metric for estimating traditional biomass, as it is easy to measure and highly correlated with tree volume and biomass [7]. However, the DBH measurement is difficult in dense plantations, buttressed stems or felled trees, limiting its applicability in some contexts. Therefore, other predictors such as stump diameter, basal diameter and proxies from remote sensing have been studied [8–10].

Measuring the diameter of stumps at 30 cm above ground level has several practical advantages. It is easier to measure on felled trees, free of complications from buttresses, and accessible in dense stands. Previous studies have demonstrated that the stump diameter is highly correlated with the DBH and biomass and can be used as a surrogate for rapid field assessments [11, 12]. In post-harvest contexts, stump diameter is often the sole measurement available, emphasizing its importance for tracking harvested volumes and carbon removals [13]. However, the diameter of the stump has been poorly studied in tropical plantation studies and most biomass models are still based on DBH [8]. Hence, systematic assessment of stump diameter across species is required especially in fast growing tropical plantations which have large role in carbon sequestration.

Bangladesh has invested heavily in plantation forestry to meet the demand for timber, rehabilitate degraded lands and increase carbon sequestration. The fast growth, adaptability and nitrogen fixing ability of *Acacia auriculiformis* and *A. mangium* make them to be some of the most important plantation species [14, 15]. The hybrid Acacia (*A. auriculiformis* × *A. mangium*) has been promoted for better growth performance and wood quality [16]. These species are widely cultivated in Bangladesh and South East Asia and are important for local livelihoods and global climate mitigation [17]. Their ability to sequester carbon has been demonstrated in recent years, with *A. mangium* often outperforming other plantation species in terms of biomass accumulation [10, 18–20]. However, most of the biomass assessments in Bangladesh are still DBH based and little exploration of stump diameter as a predictor has been done.

DBH is frequently used in biomass modeling but there has been no systematic evaluation of stump diameter for *Acacia auriculiformis*, *A. mangium* and their hybrid in Bangladesh. Generic allometric equations tend to obscure species-specific ecological variation, leading to biased estimates [13, 21]. DBH measurement is not possible in post-harvest monitoring, which means stump diameter is the only feasible measurement and creates further challenges. In addition, national and international carbon accounting frameworks require the development of accurate and scalable biomass estimation methods under diverse field conditions [4, 22].

Therefore, we hypothesize that: (1) Stump diameter has a stable biometric relationship with DBH and stem biomass for Acacia taxa. (2) Mixed effects and machine learning algorithms outperform conventional regression in capturing structural variation, yielding better predictive accuracy and generalizability. The study objectives were: (i) to develop regression models of stump diameter and DBH and

stem biomass; (ii) to evaluate the performance of the models through statistical criteria including adjusted R^2 , RMSE, AIC and Durbin-Watson statistics; (iii) to validate the models using independent data sets; and (iv) to estimate carbon stocks using stump-based biomass models following the IPCC guidelines.

The novelty of the present work is the systematic evaluation of stump diameter for several *Acacia* taxa by combining destructive sampling, regression modelling, mixed effects frameworks and machine learning approaches. The study presents a practical tool for plantation management, post-harvest monitoring and carbon accounting by showing stump diameter as a reliable surrogate for DBH. These findings have direct applications to Monitoring, Reporting and Verification (MRV) in REDD + and IPCC Tier 2/3 approaches to support the SDG 13 (Climate Action) and SDG 15 (Life on Land) through enhanced carbon accounting and sustainable forestry practices.

2 Materials and Methods

2.1 Study Area and Species Selection

The study was conducted in ten plantation sites of Sylhet Division, Bangladesh (24°53'N, 91°52'E) and it lies in the tropical South Asian monsoon zone (Fig. 1). The climate is a humid monsoon with an average annual precipitation of about 5,000 mm mainly between June and September and mean annual temperature between 24 and 26°C. The soils are mostly fertile alluvial loams, having high water holding capacity and availability of nutrients, suitable for plantation forestry [18–20].

The study included three taxa commonly used in tropical plantation programs: *Acacia auriculiformis*, *Acacia mangium* and hybrid *Acacia* (*A. auriculiformis* × *A. mangium*). These taxa are widely cultivated in South and Southeast Asia for timber, pulpwood and carbon sequestration due to their fast growth, adaptability and nitrogen fixing ability [14, 15]. The hybrid has been promoted for better growth performance and wood quality [23], and more recent studies have emphasized their role in climate change mitigation programs [4, 6]. These taxa together form the backbone of plantation forestry in Bangladesh and are an important source of timber, livelihood and carbon sequestration.

2.2 Sampling Design

We used stratified random sampling to sample representative tree size classes in the three species. In each plantation block, a random selection of 350 trees per species were selected (1,050 trees in total across all sites). At each of the ten study sites we sampled 105 trees, 35 individuals per species. Trees were selected to cover a wide range of DBH, stump diameters and stem heights and only healthy trees were included to avoid bias from disease or irregular growth [24].

To calibrate biomass equations, destructive sampling of 25 trees per species (small, medium and large diameter classes) was performed. Felled trees were cut into sections, oven dried at 105°C to constant mass, and weighed to obtain stem biomass. These destructive measurements were used to calibrate regression models to estimate biomass in non-felled trees. Destructive sampling still plays an important role in the development of species-specific regression models in tropical forestry [21, 25, 26].

2.3 Field Measurements

For each sampled tree, stump diameter (*dst*) was measured at 30 cm above ground using a diameter tape, DBH at 1.3 m, total height with a Suunto clinometer, and stem height to the first major branch. Stem biomass was determined by felling destructively sampled trees, sectioning stems, oven-drying at 105°C to constant mass, and weighing, with weights checked at 12-hour intervals until stable. These destructive measurements provided calibration data for regression models used to estimate biomass in non-felled trees [1, 2]. All measurements were taken between January and March during the dry season to minimize moisture-related variability [22].

2.4 Biomass Estimation Approaches

Two complementary approaches were used to estimate stem biomass:

(1). Traditional DBH based method: Following King et al. [27], stem biomass (SB, kg) was calculated as:

$$SB = ff \cdot \frac{\pi}{4} \cdot \rho \cdot D^2 \cdot H$$

where *ff* = form factor (ratio of actual tree volume to a cylinder with DBH and height),

ρ = wood density (kg m⁻³),

D = diameter at breast height (cm),

H = stem height (m).

This is the usual DBH based approach that is widely used in tropical forestry.

(2). Stump-based regression models: Stump diameter was assessed as a surrogate predictor by fitting twelve regression models (linear, ln-ln, polynomial, mixed effects) between stump diameter at 30 cm above ground, DBH and stem biomass. Models were calibrated with destructive sampling data (25 trees per species) and validated with adjusted R^2 , RMSE, AIC and Durbin-Watson statistics. This approach permitted to test stump diameter as a viable alternative to DBH, especially in dense stands or in post-harvest situations where DBH measurement is limited. In addition, parametric methods were used to analyze the distribution of diameters and heights, based on plantation studies that considered Normal, Log Normal and Weibull fits [28].

Advanced modeling approaches: Statistical and machine learning approaches were used in addition to the conventional DBH and stump-based regression models. Mixed effects models were used to account for random variation among species and sites and to improve generalizability across ecological contexts. Random Forest and Gradient Boosting algorithms were used to capture nonlinear relationships and interactions between predictors. We used stump diameter, DBH, stem height and wood density as predictors with stump diameter as the main predictor of interest. To prevent overfitting and to achieve a reliable accuracy of predictions, the ensemble methods were trained by cross validation.

2.5 Statistical Analysis

The descriptive statistics of stump diameter, DBH, height and biomass (mean, range, standard deviation, skewness and kurtosis) are given in Table 1. All statistical analyses were conducted using R (version 4.3.0) software [29]. Regression models were fitted with *lm()* function. Diagnostic plots were produced using *ggplot2* [30]. Descriptive statistics were estimated using the *psych* package [31].

Table 1
Descriptive statistics (mean, minimum, maximum, standard deviation, skewness, kurtosis) for stump diameter, DBH, total height, and stem height across *Acacia auriculiformis*, *A. mangium*, and hybrid *Acacia*.

Species	Variable	Mean	Min	Max	SD	Skewness	Kurtosis
Acacia	DBH (cm)	30.389	10.10	55.30	11.742	0.128	-0.866
	H (m)	9.535	6.18	14.27	1.495	0.507	-0.629
	Stem H (m)	4.717	3.16	6.74	0.807	0.448	-0.504
	d _{st} (cm)	36.807	12.56	65.10	13.221	0.090	-0.889
Mangium	DBH (cm)	27.136	10.02	52.43	9.702	0.127	-0.613
	H (m)	12.990	8.23	17.49	2.720	0.393	-0.498
	Stem H (m)	7.122	3.15	11.31	1.769	-0.065	-0.442
	d _{st} (cm)	31.305	11.52	58.46	10.825	0.034	-0.692
Hybrid	DBH (cm)	26.363	10.14	56.68	10.498	0.210	-0.886
	H (m)	15.490	9.18	22.25	4.269	0.058	-0.680
	Stem H (m)	7.738	3.28	12.77	2.128	-0.146	-0.823
	d _{st} (cm)	30.411	11.14	55.68	11.850	0.120	-1.055

In total, fourteen models (Table S1) were evaluated, four DBH models (D1–D4), eight biomass models (SB1–SB8) and two machine learning methods (Random Forest, Gradient Boosting). All log transformations were natural logs (ln). The predictive performance of the model was assessed by adjusted R^2 , RMSE, AIC, average deviation (%), correction factor (CF) and Durbin–Watson (DW) statistics. The regression coefficients were tested by t tests at significance levels $p < 0.01$, 0.001 and 0.0001 . The residual diagnostics such as Q–Q plots, and the homoscedasticity check were conducted to verify normality and the stability of the variance [22, 32]. For unbiased estimates of predictive accuracy across species and pooled data, these analyses were independently validated.

We used the *lme4* package in R [33] to fit mixed effects models with species as a random effect. Random Forest models were implemented using the *randomForest* package [34] and Gradient Boosting models were implemented using the *gbm* package [35]. The predictive performance was assessed using adjusted R^2 , RMSE, AIC (when applicable) and cross validation error (%). Variable importance measures were computed for Random Forest and Gradient Boosting to assess the relative importance of predictors. Q-Q plots and homoscedasticity checks were used to diagnose normality and variance stability residuals.

2.6 Validation

We have implemented a two-level validation so that the evaluation is sound and unbiased. First, the data set was divided into calibration and validation subsets. Calibration models were developed for 75 destructively sampled trees (25 per species) in small, medium and large diameter classes. The remaining trees ($n = 975$) were independently validated and removed from the model calibration. This ensured that the predictive accuracy was assessed on trees not used in the model development [1, 2].

Second, we used cross-validation procedures to assess generalizability across species and sites. We also used established procedures [33, 36] to trail regression, mixed effects and standard ML models with fivefold cross validation stratified by species. Each fold was rotated so that each subset was used as a validation set to minimize bias from site-specific or species-specific effects.

Validation measures were adjusted R^2 , RMSE, standard error of estimate (SEE), paired t tests and 95% confidence intervals [7]. There was no significant difference between predicted and observed means ($p > 0.05$) confirming that the predictions were unbiased. Low values of SEE were noted across taxa and residual plots showed clustering around zero indicating high precision. Cross validation error rates also validated random Forest and Gradient Boosting models, as consistent with recent applications of biomass modeling in tropical forestry [34, 35, 37, 38]. This explicit validation design with independent data sets and cross validation confirms that stump-based models are generalizable across species and sites and not restricted to the calibration sample.

2.7 Carbon Stock Estimation

To convert stem biomass estimates into carbon stock, species specific conversion factors were used (*A. auriculiformis* = 0.475, *A. mangium* = 0.480, hybrid Acacia = 0.485). These values exhibit variation in wood chemistry among taxa and reduce bias associated with reliance on IPCC defaults [3, 5]. Carbon stocks were estimated at two levels: (i) species specific estimates based on mean stem biomass and (ii) combined stand level estimates by pooling data across taxa and scaling to plantation stocking densities derived from field records. The technique can combine the two levels of analysis to quantify the collective role of taxa in plantation carbon sequestration and to capture ecological differences among taxa.

2.8 Quality Control

All measurements were repeated, and those differing by more than 0.5 cm (diameter) or 0.2 m (height) were repeated. Samples were dried in an oven to constant mass (48–72 h at 105°C) with weights checked at 12 h intervals. Instruments were calibrated on a daily basis and data entry was cross-checked by two independent researchers. Biologically plausible outliers were retained. This robust quality assurance protocol is consistent with best practice in forest mensuration and biomass estimation [39, 40].

3 Results

3.1 Descriptive statistics

Among 1,050 sampled trees, species varied widely in stump diameter, DBH, total height and stem height (Table 1). *A. auriculiformis* had the highest mean DBH (30.4cm) and stump diameter (36.8cm) while hybrid Acacia had the highest mean height (15.5m). Distributions were characterized by low skewness and kurtosis, indicative of approximate normality and representative sampling across size classes.

3.2 Regression models for DBH

The diameter of the stump was highly correlated with DBH among species (Fig. 2). The ln–ln regression (D2) provided adjusted R^2 values of > 0.98 across all taxa (Table 2). The range of RMSE values was 0.048–0.074. The polynomial models (D3) gave only small improvements but at the expense of increasing complexity. Mixed effects models (D4) further reduced bias (Figure S1) and had conditional R^2 values of 0.98 and Durbin–Watson statistics near 2.0, confirming independence of residuals. Combined species regressions (Table S2) showed the ln–ln model to be robust, with adjusted $R^2 = 0.985$ and lowest AIC values (–884.42). The results support our first hypothesis, showing that the ln–ln regression between stump diameter and DBH was highly stable ($R^2 > 0.98$) for the three Acacia taxa, with low RMSE values and unbiased residuals.

Table 2

Species-specific regression results for *A. auriculiformis*, *A. mangium*, and hybrid Acacia. Performance metrics (Adjusted R^2 , RMSE, AIC, average deviation, correction factor, Durbin–Watson) for stump-based regression models predicting DBH.

Model	Species	Estimated coefficients			RMSE	F	Adjusted R^2	AIC	Average deviation (%)	CF	DW
		β_0	β_1	β_2							
D1	Acacia	-2.209***	0.885***		1.468	12940	0.9849	725.18	4.290	NA	1.977
	Mangium	-0.642*	0.887***		1.331	10380	0.9812	685.86	4.066	NA	1.999
	Hybrid	-0.207	0.872***		1.179	15310	0.9872	637.33	3.680	NA	1.843
D2	Acacia	-0.530***	1.091***		0.059	11240	0.9826	-560.00	4.306	1.0017	2.008
	Mangium	-0.201***	1.016***		0.051	11980	0.9837	-619.87	4.023	1.0012	2.055
	Hybrid	-0.154***	1.002***		0.048	16380	0.9880	-646.12	3.680	1.0011	1.949
D3	Acacia	1.535***	0.069***	-0.00049***	0.063	4903	0.9801	-532.17	4.692	1.0019	1.875
	Mangium	1.639***	0.069***	-0.00053***	0.054	5381	0.9818	-597.82	4.184	1.0014	2.001
	Hybrid	1.622***	0.071***	-0.00056***	0.050	7532	0.9870	-628.57	4.020	1.0012	1.633
D4	Acacia	-0.476***	1.073***		0.074	8216	0.9802	-473.72	4.264	1.0032	1.731
	Mangium	-0.371***	1.036***		0.061	9417	0.9782	-582.41	4.715	1.0027	1.872
	Hybrid	-0.165***	1.015***		0.057	7184	0.9807	-631.64	4.916	1.0019	1.693

* $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$

3.3 Regression models for stem biomass

DBH based biomass models (SB1–SB4) explained significant variation but stump-based models (SB5–SB8) performed equally well or better (Table 3). The ln–ln stump-based model (SB6) was parsimonious and produced adjusted R^2 values of 0.945–0.968 across species and RMSE values of 0.196–0.222. The residual plots (Figure S2) clustered around zero and the observed versus predicted plots (Fig. 3) were close to the 1:1 line, confirming the predictive accuracy. Mixed effects stump-based models (SB8) further reduced bias especially for hybrid Acacia. Combined species regressions (Table S2) confirmed SB6 as the most robust stump-based framework, with adjusted $R^2=0.955$ and low RMSE (0.269).

Table 3

Species-specific regression results for *A. auriculiformis*, *A. mangium*, and hybrid Acacia. Performance indicators (Adjusted R^2 , RMSE, AIC, average deviation, correction factor, Durbin–Watson) of DBH based and stump-based regression models for predicting stem biomass.

Model	Species	Estimated coefficients			RMSE	F	Adjusted R^2	AIC	Average deviation (%)	CF	DW
		β_0	β_1	β_2							
SB1	Acacia	2.663***	0.074***		0.263	2231	0.9181	36.66	22.710	1.0350	1.850
	Mangium	2.514***	0.085***		0.292	1580	0.8881	79.19	25.351	1.0435	1.879
	Hybrid	2.560***	0.089***		0.289	2061	0.9119	74.64	25.346	1.0425	1.853
SB2	Acacia	-1.993***	2.082***		0.155	6802	0.9716	-175.00	12.981	1.0120	2.119
	Mangium	-2.093***	2.142**		0.193	3883	0.9512	-86.98	16.284	1.0187	2.017
	Hybrid	-2.086***	2.199**		0.182	5472	0.9649	-109.38	15.784	1.0167	2.037
SB3	Acacia	1.522***	0.160***	-0.0013***	0.171	2750	0.9651	-132.81	14.628	1.0148	2.004
	Mangium	1.177***	0.195***	-0.0019***	0.199	1809	0.9478	-72.57	17.028	1.0200	1.901
	Hybrid	1.266***	0.201***	-0.0020***	0.196	2353	0.9594	-79.35	22.868	1.0193	1.853
SB4	Acacia	-1.822***	2.028***		0.174	5732	0.9631	-162.61	13.738	1.0175	2.132
	Mangium	-2.013***	2.073***		0.199	4761	0.9482	-102.45	18.618	1.0207	1.967
	Hybrid	-2.173***	2.264***		0.194	4525	0.9531	-89.36	20.739	1.0198	1.871
SB5	Acacia	2.505***	0.066***		0.279	1951	0.9074	61.17	24.238	1.0397	1.815
	Mangium	2.450***	0.075***		0.300	1484	0.8817	90.24	26.170	1.0460	1.825
	Hybrid	2.536***	0.078***		0.298	1923	0.9062	87.30	25.773	1.0454	1.800
SB6	Acacia	-2.992***	2.245***		0.196	4182	0.9676	-81.20	16.507	1.0193	2.070
	Mangium	-2.519***	2.175***		0.222	2882	0.9454	-30.69	18.308	1.0249	2.002
	Hybrid	-2.426***	2.205***		0.207	4186	0.9546	-57.95	17.266	1.0217	2.031
SB7	Acacia	1.222***	0.144***	-0.0010***	0.203	1926	0.9508	-64.49	17.597	1.0209	2.098
	Mangium	1.154***	0.169***	-0.0014***	0.227	1377	0.9326	-21.19	18.691	1.0260	2.009
	Hybrid	1.289***	0.171***	-0.0015***	0.218	1883	0.9498	-36.80	18.737	1.0240	1.825
SB8	Acacia	-1.947***	2.051***		0.215	3743	0.9576	-57.71	20.563	1.0237	2.096
	Mangium	-1.819***	2.149***		0.284	2314	0.9401	-26.82	21.683	1.0208	2.037
	Hybrid	-1.339***	2.184***		0.279	3512	0.9451	-48.73	19.371	1.0225	2.065
* $P < 0.01$, ** $P < 0.001$, *** $P < 0.0001$											

3.4 Combined regression performance

When species were combined, stump diameter continued to be a strong predictor of DBH and stem biomass (Table S2). The ln-ln regression (D2) was consistently superior to linear and polynomial alternatives, while mixed effects models (D4, SB8) reduced site level bias. The histograms of the residual distribution (Figure S3) showed that residuals were balanced for regression and mixed effects models while Gradient Boosting showed a slight tendency to overfit. The comparison of performance indicators (Fig. 4) corroborated the advantage of the ln-ln and mixed effects frameworks across taxa.

3.5 Validation

Independent validation confirmed unbiased predictive accuracy for both DBH and biomass models (Table 4). Observed and predicted means were not significantly different (paired t tests, $p > 0.05$) and had narrow confidence intervals and low SEE. The SEE values for the ln-ln regression for DBH (D2) were between 0.283 and 0.588, while the SEE values for the biomass model SB2 and SB6 were between 2.058 and 4.971. Points clustered close to the 1:1 line in plots of observed versus predicted values suggested high precision (Fig. 3). Stump diameter was the most important predictor in regression, mixed effects and machine learning frameworks (Figure S3).

Table 4

Validation of observed versus predicted DBH (D2 model) and stem biomass (SB2 and SB6 models) for individual species and the combined dataset. Mean values, standard deviation, standard error of estimate, t test results and 95% confidence intervals are presented.

Model	Species	Parameter	Observed	Predicted	SD	SEE	t	significance
D2	Acacia	Mean	30.389	28.655	11.742	0.528	3.363	0.225
		95% CI lower limit	28.752	26.719				
		95% CI upper limit	31.904	32.592				
D2	Mangium	Mean	27.136	25.606	9.702	0.324	4.990	0.353
		95% CI lower limit	25.783	24.379				
		95% CI upper limit	28.489	26.832				
D2	Hybrid	Mean	26.328	29.154	10.499	0.588	-5.095	0.106
		95% CI lower limit	24.899	27.120				
		95% CI upper limit	27.827	31.188				
D2	Combined	Mean	27.963	27.805	10.805	0.283	0.558	0.577
		95% CI lower limit	27.097	26.781				
		95% CI upper limit	28.829	28.828				
SB2	Acacia	Mean	196.424	197.077	38.298	2.708	-0.241	0.405
		95% CI lower limit	175.957	177.103				
		95% CI upper limit	216.892	217.052				
SB2	Mangium	Mean	168.042	170.476	36.716	2.596	-0.937	0.175
		95% CI lower limit	152.139	153.864				
		95% CI upper limit	183.946	187.088				
SB2	Hybrid	Mean	199.702	202.134	44.127	3.120	-0.780	0.218
		95% CI lower limit	178.119	180.378				
		95% CI upper limit	221.284	223.890				
SB2	Combined	Mean	188.056	186.264	65.148	2.058	0.870	0.384
		95% CI lower limit	176.819	175.111				
		95% CI upper limit	199.293	197.417				
SB6	Acacia	Mean	196.425	198.478	76.785	4.279	-10.022	0.143
		95% CI lower limit	175.957	177.145				
		95% CI upper limit	216.892	219.811				
SB6	Mangium	Mean	168.042	165.520	64.057	2.782	1.999	0.106
		95% CI lower limit	152.139	147.407				
		95% CI upper limit	183.946	179.632				
SB6	Hybrid	Mean	199.702	195.965	84.784	4.971	10.407	0.127
		95% CI lower limit	178.119	174.684				
		95% CI upper limit	221.284	214.246				
SB6	Combined	Mean	188.056	186.988	81.148	2.375	1.715	0.286
* $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$								

Model	Species	Parameter	Observed	Predicted	SD	SEE	t	significance
		95% CI lower limit	176.819	173.205				
		95% CI upper limit	199.293	195.770				
* $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$								

3.6 Machine learning approaches

The Random Forest and Gradient Boosting models provided complementary insights (Table 5). Random Forest consistently identified stump diameter as the most important predictor of stem biomass, with high values of %IncMSE and node purity (Fig. 5a). Conversely, the highest relative importance was assigned to DBH (85%) by Gradient Boosting, followed by tree height and stem height (Fig. 5b). Gradient Boosting had signs of overfitting in the learning curves, although it achieved high apparent accuracy. Performance indicators in comparison (Fig. 4) showed the stability of Random Forest, further proving the predictive supremacy of stump diameter. These results confirm the second hypothesis: mixed effects models reduced prediction bias, especially for hybrid Acacia, while Random Forest consistently identified stump diameter as the most important predictor of stem biomass.

Table 5
Variable importance ranking from Random Forest (RF) and Gradient Boosting (GBM) models. RF importance by %IncMSE and node purity. GBM importance by relative influence.

Variable	%IncMSE (RF)	IncNodePurity (RF)	Relative Influence (GBM)	Dominant Predictor
DBH	34.59	4,780,609.7	85.02	GBM
StumpDiameter	32.82	4,643,051.2	4.00	RF
TreeHeight	28.65	964,511.2	6.22	–
StemHeight	26.01	1,190,686.6	4.76	–

3.7 Carbon stock estimation

Regression fits for species specific models (Fig. 6a) and all species combined (Fig. 6b) demonstrated good relationships between stump diameter and stem biomass with adjusted $R^2 > 0.95$ providing support for stump diameter as a feasible surrogate for carbon accounting. Carbon stock estimates showed species specific differences (Fig. 7). Following the Hybrid Acacia, *A. mangium* and *A. auriculiformis* had the next highest average carbon stock per hectare. Error bars indicated similar variation among sites. The pooled estimates at stand level confirmed that Acacia plantations contributed substantially to carbon sequestration and, therefore, to climate change mitigation.

4 Discussion

4.1 Stump diameter as a surrogate for DBH

Our findings indicate that stump diameter is a good proxy for DBH in *A. auriculiformis*, *A. mangium* and hybrid Acacia. The significant allometric relationship observed confirms that stump measurements can be used as a proxy for DBH when breast height measurements are not possible (e.g. dense understory, post-harvest stands). This approach alleviates operational constraints and is in line with evidence from Southeast Asia advocating hybrid Acacia, for its fast growth and adaptability [16, 41]. Similar conclusions have been reached in wider tropical contexts, where stump or basal diameter has been trialed as a proxy for DBH [25, 40]. Our first hypothesis is supported by the strong relationship between stump diameter and DBH across species, indicating that stump diameter can be a good proxy where the measurement of DBH is not feasible.

4.2 Predictive performance of stump-based biomass models

Stump based biomass models were comparable to, and in some cases better than, conventional DBH based models. Stump diameter is a practical predictor for biomass estimation given its parsimonious structure and consistent accuracy. Mixed effects frameworks improved generalizability further, especially for hybrid Acacia, indicating the value of species-specific modeling. These results align with destructive sampling studies in Vietnam to develop allometric equations for Acacia hybrids using DBH and height as predictors of biomass and carbon stocks [13, 42]. Our study addresses a methodological gap that has not been addressed by previous studies, including a systematic evaluation of stump diameter as a promising and robust surrogate in dense stands and immediately after harvest. This is consistent with the allometric models generally employed in tropical forests [2, 11]. The explicit two-tier validation design integrating

independent datasets with cross validation demonstrated that stump-based models are generalizable across species and sites, reinforcing their usefulness for operational forestry and carbon accounting.

4.3 Machine learning confirmation and limitations

The ensemble methods also confirmed stump diameter as an important predictor. The Random Forest always found stump diameter to be the most important variable, while the Gradient Boosting found DBH, but it appeared to be over fit. This underscores the necessity of a rigorous implementation of machine learning in forestry: while these techniques are capable of capturing complex relations, interpretability and generalizability are still of great importance for operational use [35, 37]. This view is recently supported by machine learning applications in tropical forestry with promise and caution in biomass estimation [17, 22]. Our second hypothesis was also confirmed: mixed effects and Random Forest models improved predictive accuracy compared to conventional regression, while Gradient Boosting showed the risk of overfitting in more complex algorithms.

4.4 Species-specific differences

Carbon stock estimates were significantly different across species with hybrid Acacia highest than others in carbon storage. These differences are consistent with ecological variation in growth rates, wood density and stem form, consistent with biodiversity–function relationships in tropical forests [43]. The increased performance of hybrid Acacia suggests its potential utility in climate mitigation programs, while *A. auriculiformis* and *A. mangium* remain important for diversified timber and carbon portfolios [4, 6]. These results complement earlier studies on diversity-productivity relationships in Bangladesh [44] emphasizing the role of species composition in explaining biomass accumulation and carbon dynamics. Similar carbon dynamics have been reported in plantation systems in regional studies [18, 45].

4.5 Implications

The ability to estimate DBH and biomass from the stump diameter has important practical implications. Rapid assessments can be made without clearing vegetation in dense stands and stump measurements in harvested stands can be used to reconstruct stand biomass and carbon stocks. This supports Monitoring, Reporting and Verification (MRV) under REDD + and IPCC Tier 2/3 frameworks [3, 5]. The combination of stump-based models with state-of-the-art statistical and machine learning approaches enables forestry practitioners to estimate biomass in a precise, efficient and scalable manner across species and sites. Moreover, accurate estimation of biomass across different disturbance regimes is important because gradients in forest structure and regeneration have a strong effect on carbon accounting outcomes [3, 46]. This approach is consistent with the best practices of tropical forestry where hybrid Acacia is increasingly recognized as a fundamental species for timber supply and carbon sequestration [14, 15].

Therefore, these applications make the stump diameter a practical and scalable tool for biomass reconstruction and carbon accounting in tropical plantation systems. Stump based models reduce measurement constraints and enable reliable post-harvest monitoring which improves operational forestry and contributes to international climate and biodiversity targets. This study contributes to SDG 13 (Climate Action) by enhancing greenhouse gas inventories and SDG 15 (Life on Land) through sustainable management of plantations, strengthening the contribution of tropical plantations to global climate mitigation efforts.

5 Conclusion

This study suggest that stump diameter is a good surrogate for estimating DBH and stem biomass in *Acacia auriculiformis*, *A. mangium* and hybrid plantations in Bangladesh. Biometric relationships of stump diameter with DBH and biomass were stable and predicted with high precision across the studied species. Mixed effects and machine learning approaches also showed improvements in model performance. Random Forest reconfirmed stump diameter as the major predictor, while Gradient Boosting emphasized the need to avoid overfitting. Independent validation confirmed unbiased predictions, demonstrating the robustness of stump-based models for practical applications. Estimates of carbon stocks showed species specific differences and hybrid Acacia had better performance than its parents, which underlines its potential role in plantation forestry and climate change mitigation. This study contributes to tropical forestry with operationally relevant methods combining destructive sampling, regression modeling, mixed effects frameworks and machine learning. The ability to estimate stand biomass and carbon stocks from stump measurements allows for rapid assessment in dense stands and reliable post-harvest monitoring. The results present evidence for MRV under REDD + and the IPCC Tier 2/3 frameworks, and constitute a scalable tool for national greenhouse gas inventories and sustainable forest management. The work contributes to international climate and biodiversity targets under SDG 13 and SDG 15, by improving the scientific basis for carbon accounting and encouraging evidence based tropical plantation management.

Declarations

Ethics approval and consent to participate

The study was carried out in the plantation forests of *Acacia auriculiformis*, *Acacia mangium*, and hybrid *Acacia* (*A. auriculiformis* × *A. mangium*) in Sylhet Forest Division, Bangladesh. These species were planted, not wild, and measurements were done with national forestry guidelines. Permission for field data collection was obtained from the Bangladesh Forest Department. The species were identified and confirmed by Niamjit Das, Department of Forestry and Environmental Science, Shahjalal University of Science and Technology. In this study, voucher specimen was not collected for deposition. Moreover, this study does not contain any studies with human participants or animals performed by any of the authors.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contribution

ND designed and conceived the study, coordinated the fieldwork, performed measurements and sampling and data analyses including statistical modelling, and wrote the manuscript. MQC provided methodological guidance, data interpretation, and critically revised the manuscript. All authors have read and approved the final manuscript.

Acknowledgement

The authors are grateful to Bangladesh Forest Department for granting us a permission for field work and offering assistance in field measurements.

Data Availability

All data underlying the results presented in this study are available from the corresponding author upon on request for verification and further analysis.

References

1. Brown S. Estimating biomass and biomass change of tropical forests: a primer. FAO Forestry Paper 134. Rome: Food and Agriculture Organization of the United Nations; 1997. p. 55.
2. Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WBC, et al. Improved allometric models to estimate the aboveground biomass of tropical trees. *Glob Change Biol*. 2014;20:3177–90. <https://doi.org/10.1111/gcb.12629>.
3. Pan Y, Birdsey RA, Fang J, Houghton R, Kauppi PE, Kurz WA, et al. A large and persistent carbon sink in the world's forests. *Science*. 2011;333:988–93. <https://doi.org/10.1126/science.1201609>.
4. Grassi G, House J, Dentener F, Federici S, den Elzen M, Penman J. The key role of forests in meeting climate targets requires science for credible mitigation. *Nat Clim Change*. 2017;7:220–6. <https://doi.org/10.1038/nclimate3227>.
5. IPCC. *2006 IPCC guidelines for national greenhouse gas inventories*. Vol. 4: Agriculture, forestry and other land use. Hayama: Institute for Global Environmental Strategies; 2006.
6. Lewis SL, Wheeler CE, Mitchard ETA, Koch A. Restoring natural forests is the best way to remove atmospheric carbon. *Nature*. 2019;568:25–8. <https://doi.org/10.1038/d41586-019-01026-8>.

7. Avery TE, Burkhardt HE. Forest measurements. 6th ed. Long Grove (IL): Waveland; 2015. p. 456.
8. Návar J. Allometric equations for tree species and carbon stocks for forests of northwestern Mexico. *Ecol Manage.* 2009;257:427–34. <https://doi.org/10.1016/j.foreco.2008.09.028>.
9. Latifah S, Purwoko A, Hartini KS, Fachrudin KA. Allometric models to estimate the aboveground biomass of forest: a literature review. *IOP Conf Ser Mater Sci Eng.* 2021;1122:012047. <https://doi.org/10.1088/1757-899X/1122/1/012047>.
10. Reta GT, Tolera M, Mokria M. Species-specific allometric models for estimating aboveground biomass and carbon stocks of plantation forests in north central Ethiopia. *Sci Rep.* 2026;16:48435. <https://doi.org/10.1038/s41598-026-48435-0>.
11. Ketterings QM, Coe R, Van Noordwijk M, Ambagau Y, Palm CA. Reducing uncertainty in the use of allometric biomass equations for predicting aboveground tree biomass in mixed secondary forests. *Ecol Manage.* 2001;146:199–209. [https://doi.org/10.1016/S0378-1127\(00\)00460-6](https://doi.org/10.1016/S0378-1127(00)00460-6).
12. Litton CM, Kauffman JB. Allometric models for predicting aboveground biomass in two widespread woody plants in Hawaii. *Biotropica.* 2008;40:313–20. <https://doi.org/10.1111/j.1744-7429.2007.00383.x>.
13. Picard N, Saint-André L, Henry M. *Manual for building tree volume and biomass allometric equations: from field measurement to prediction*. Rome: Food and Agriculture Organization of the United Nations; Montpellier: Centre de Coopération Internationale en Recherche Agronomique pour le Développement; 2012. p. 215.
14. Krisnawati H, Kallio M, Kanninen M. *Acacia mangium Willd.: ecology, silviculture and productivity*. CIFOR Occasional Paper No. 62. Bogor (Indonesia. Center for International Forestry Research; 2011. <https://doi.org/10.17528/cifor/003392>.
15. Midgley SJ, Turnbull JW. Domestication and use of Australian acacias: case studies of five important species. *Aust Syst Bot.* 2003;16:89–102. <https://doi.org/10.1071/SB01038>.
16. Sunarti S, Nirsatmanto A, Kartikawati NK, Putri AI, Herawan T, Haryjanto L, et al. Introducing a new variety of interspecific *Acacia* hybrid (*Acacia mangium* × *A. auriculiformis*) for renewable biomass energy. *IOP Conf Ser Earth Environ Sci.* 2023;1182:012020. <https://doi.org/10.1088/1755-1315/1182/1/012020>.
17. Hoque MZ, Cui S, Islam I, Xu L, Ding S. Dynamics of plantation forest development and ecosystem carbon storage change in coastal Bangladesh. *Ecol Indic.* 2021;130:107954. <https://doi.org/10.1016/j.ecolind.2021.107954>.
18. Biswas M, Hasan M. Measurement of aboveground carbon stocks of roadside agroforestry plantation at Sadar Upazila of Mymensingh District in Bangladesh. *J Bangladesh Agric Univ.* 2020;1:1–8. <https://doi.org/10.5455/JBAU.91198>.
19. Phan SM, Pham D, Chu C. Main drivers of productivity of *Acacia mangium* plantations in Vietnam. *Ecol Manage.* 2024;561:121859. <https://doi.org/10.1016/j.foreco.2024.121859>.
20. Chowdhury MIH, Rakib MH. Phytosociology and carbon sequestration potential of tropical forest landscape: a case from Northwest Chittagong, Bangladesh. *Asian J For.* 2024;8:203–15. <https://doi.org/10.13057/asianjfor/r080203>.
21. Henry M, Picard N, Trotta C, Manlay R, Valentini R, Bernoux M, Saint-André L. Estimating tree biomass of sub-Saharan African forests: a review of available allometric equations. *Silva Fenn.* 2011;45:38. <https://doi.org/10.14214/sf.38>.
22. Nguyen TP, Nguyen PK, Nguyen HN, Tran TD, Pham GT, Le TH, et al. Evaluation of statistical and machine learning models using satellite data to estimate aboveground biomass: a study in Vietnam tropical forests. *Sci Technol.* 2024;20:370–82. <https://doi.org/10.1080/21580103.2024.2409211>.
23. Sedgley M, Harbard J, Smith R, Wickneswari R, Griffin A. Reproductive biology and interspecific hybridization of *Acacia mangium* and *Acacia auriculiformis* A. Cunn. ex Benth (Leguminosae, Mimosoideae). *Aust J Bot.* 1992;40:37–48. <https://doi.org/10.1071/BT9920037>.
24. Burkhardt HE, Avery TE, Bullock BP. Forest measurements. 6th ed. Long Grove (IL): Waveland; 2018. p. 456.
25. Basuki TM, van Laake PE, Skidmore AK, Hussin YA. Allometric equations for estimating the aboveground biomass in tropical lowland dipterocarp forests. *Ecol Manage.* 2009;257:1684–94. <https://doi.org/10.1016/j.foreco.2009.01.027>.
26. Das N. Allometric modeling for leaf area and leaf biomass estimation of *Swietenia mahagoni* in the north eastern region of Bangladesh. *J Environ Sci.* 2014;30:351–61. <https://doi.org/10.7747/JFES.2014.30.4.351>.
27. King DA, Davies SJ, Tan S, Noor NSM. The role of wood density and stem support costs in the growth and mortality of tropical trees. *J Ecol.* 2006;94:670–80. <https://doi.org/10.1111/j.1365-2745.2006.01112.x>.
28. Das N, Mahapatra CK, Biswas SK, Das P, Majumdar A. Suitability of the Normal, Log Normal and Weibull distributions for modeling diameter and height distributions of *Swietenia mahagoni* plantations in Bangladesh. *J Biol Nat.* 2018;8(4):146–55.
29. R Core Team. R: a language and environment for statistical computing. Version 4.5.0. Vienna: R Foundation for Statistical Computing. 2025. Available from: <https://www.R-project.org/>

30. Wickham H. *ggplot2*. Use R! Cham: Springer International Publishing; 2016. p. 213. <https://doi.org/10.1007/978-3-319-24277-4>.
31. Revelle W. Package Psych: procedures for psychological, psychometric, and personality research. 2022. Available from: <https://personality-project.org/r/psych>
32. Brown S, Lugo AE. Biomass of tropical forests: a new estimate based on forest volumes. *Science*. 1984;223:1290–3. <https://doi.org/10.1126/science.223.4642.1290>.
33. Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed effects models using lme4. *J Stat Softw*. 2015;67(1):1–48. <https://doi.org/10.18637/jss.v067.i01>.
34. Liaw A, Wiener M. Classification and regression by randomForest. *R News*. 2002;2(3):18–22. Available from: <http://CRAN.R-project.org/doc/Rnews/>
35. Ridgeway G. Generalized boosted models: a guide to the GBM package. 2024. Available from: <https://cran.r-project.org/web/packages/gbm/vignettes/gbm.pdf>
36. Kohavi R. Wrappers for performance enhancement and oblivious decision graphs. [PhD thesis]. Stanford (CA): Stanford University, Computer Science Department; 1995. p. 170.
37. Breiman L. Random forests. *Mach Learn*. 2001;45:5–32. <https://doi.org/10.1023/A:1010933404324>.
38. Rajput P. Machine learning approach for forest biomass modelling with in situ and remote sensing data in Narmadapuram, central India. *Model Earth Syst Environ*. 2025;11:350. <https://doi.org/10.1007/s40808-025-02527-4>.
39. Clark DB, Kellner JR. Tropical forest biomass estimation and the fallacy of misplaced concreteness. *J Veg Sci*. 2012;23:1191–6. <https://doi.org/10.1111/j.1654-1103.2012.01471.x>.
40. Sileshi GW. A critical review of forest biomass estimation models, common mistakes and corrective measures. *Ecol Manage*. 2014;329:237–54. <https://doi.org/10.1016/j.foreco.2014.06.026>.
41. Newaz MS, Kamaluddin M, Rashid AZMM. Growth and yield prediction models for hybrid *Acacia* (*A. auriculiformis* × *A. mangium*) grown in the plantations of Bangladesh. *Pak J Biol Sci*. 2005;8:1137–41. <https://doi.org/10.3923/pjbs.2005.1137.1141>.
42. Doan TNM, Vu VM, Ruano I, Bravo F. Disentangling the relationship of aboveground biomass, structure and tree diversity in a mixed *Acacia* plantation in Northern Vietnam. *Eur J Res*. 2025;144:941–61. <https://doi.org/10.1007/s10342-025-01776-3>.
43. Das N. Biodiversity in forest ecosystems: patterns, drivers, and conservation strategies. New York: Nova Science; 2025. p. 320. <https://doi.org/10.52305/AZJY2712>.
44. Das N, Sarker SK. Tree species diversity and productivity relationship in the central region of Bangladesh. *J For*. 2015;2(2):24–33. <https://doi.org/10.18488/journal.101/2015.2.2/101.2.24.33>.
45. Ma J, Shugart HH, Yan X, Cao C, Wu S, Fang J. Evaluating carbon fluxes of global forest ecosystems by using an individual tree-based model FORCCHN. *Sci Total Environ*. 2017;586:939–51. <https://doi.org/10.1016/j.scitotenv.2017.02.073>.
46. Das N. Disturbance gradients reshape biodiversity, structure, and regeneration in *Sal* (*Shorea robusta*) forests of Dharmapur National Park, Bangladesh. *Trees People*. 2026;23:101148. <https://doi.org/10.1016/j.tfp.2026.101148>.

Figures

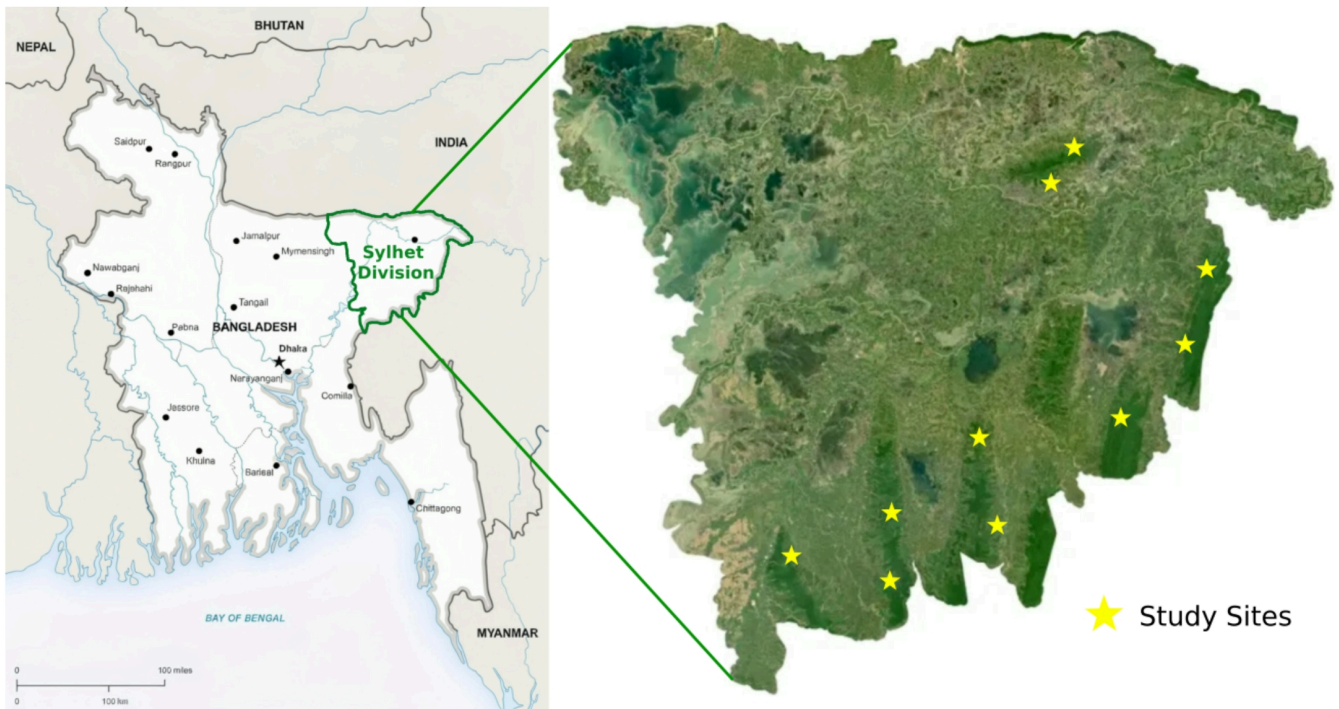


Figure 1

Location of ten study sites in the plantation forests of Sylhet Division, Bangladesh

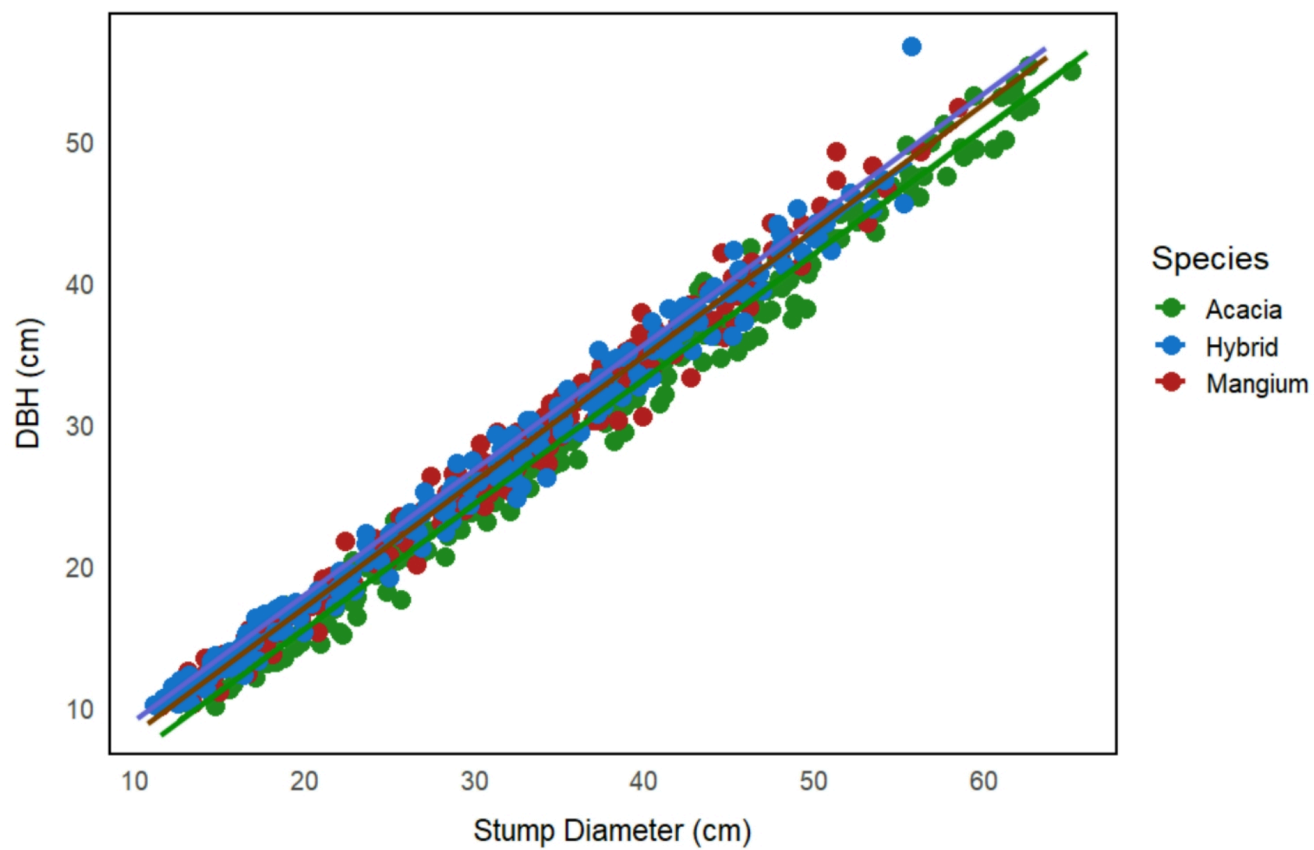


Figure 2

Relationship between stump diameter and DBH for three acacia species. Regression lines for the ln-ln model (D2)

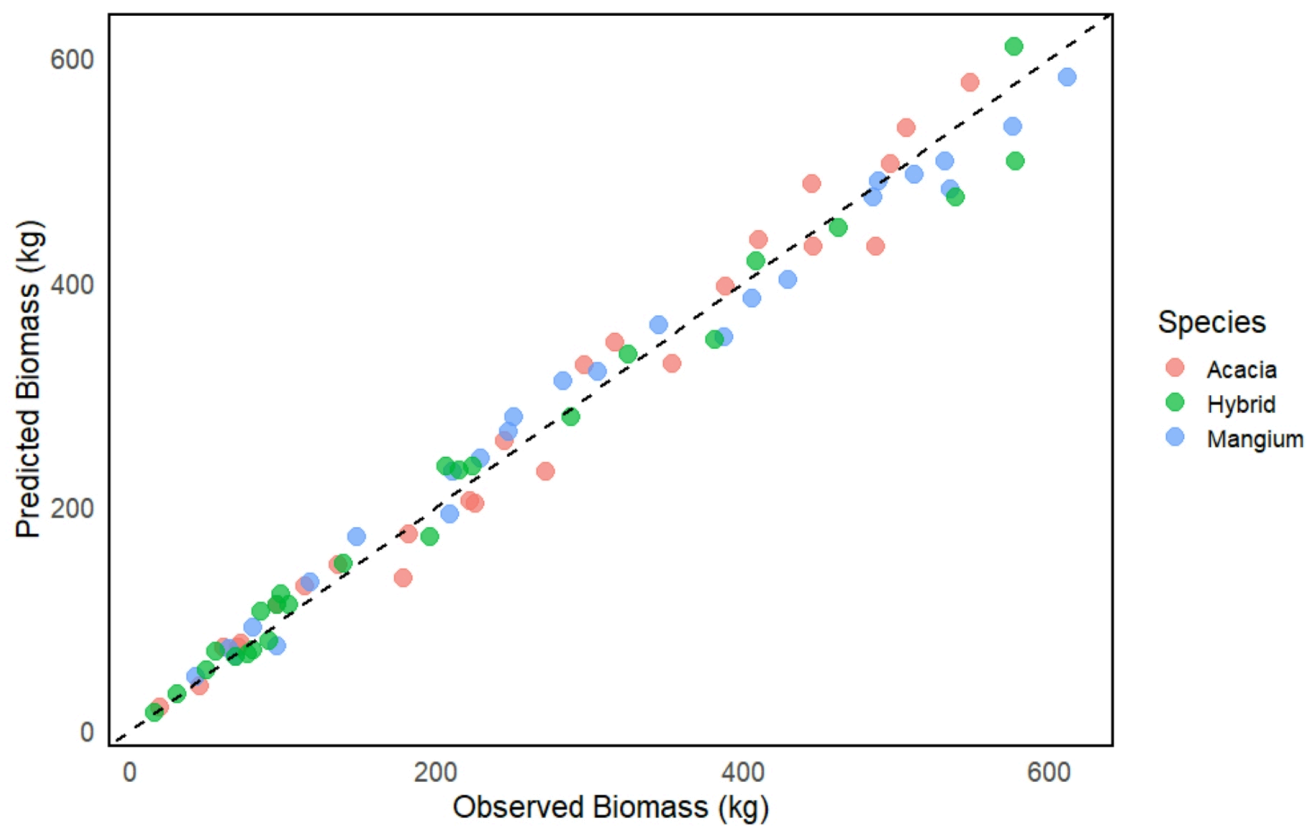


Figure 3

Observed vs. predicted values of stem biomass for stump-based models, consistent with the 1:1 line

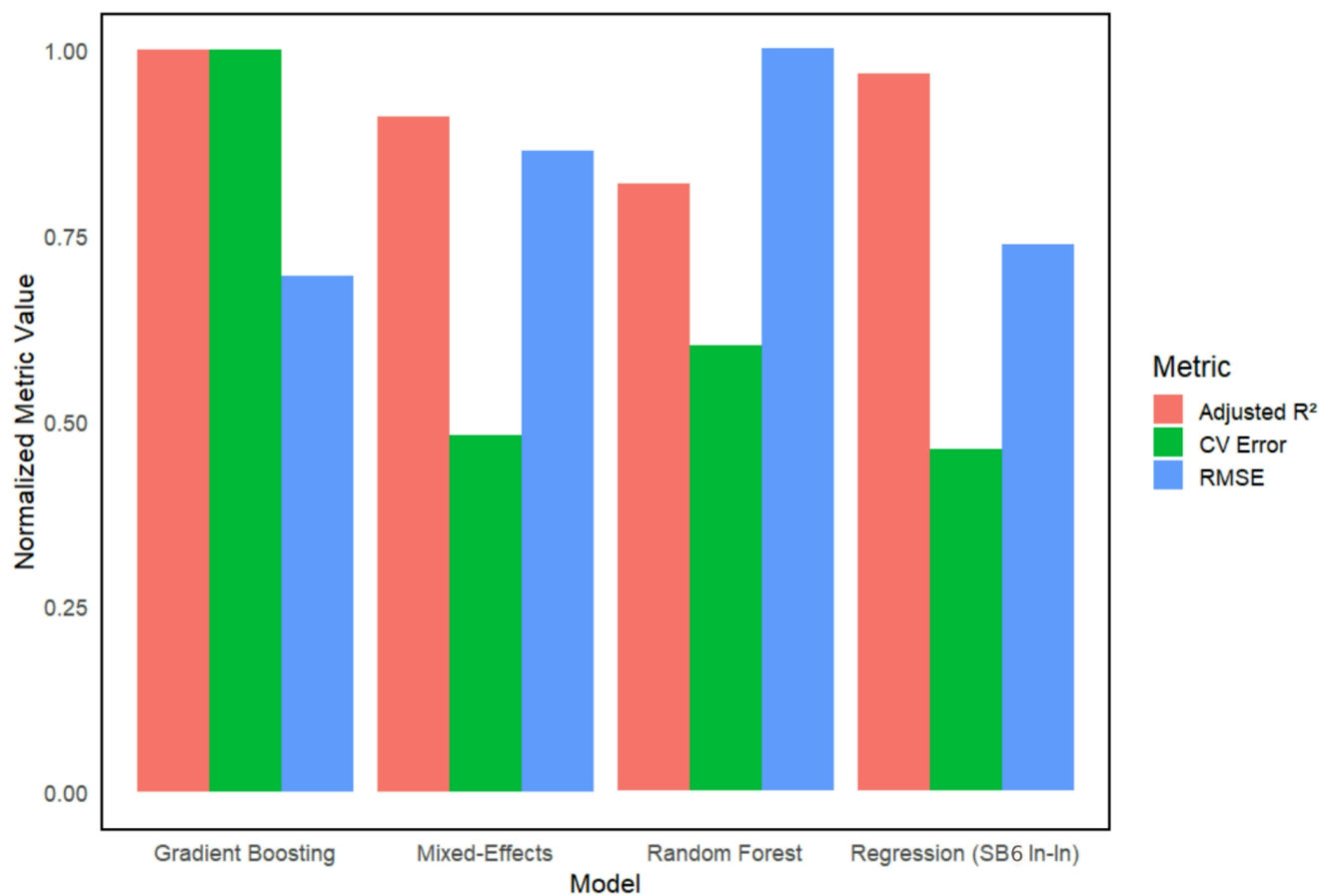


Figure 4

Comparison of performance indicators between regression, mixed effects and standard ML models

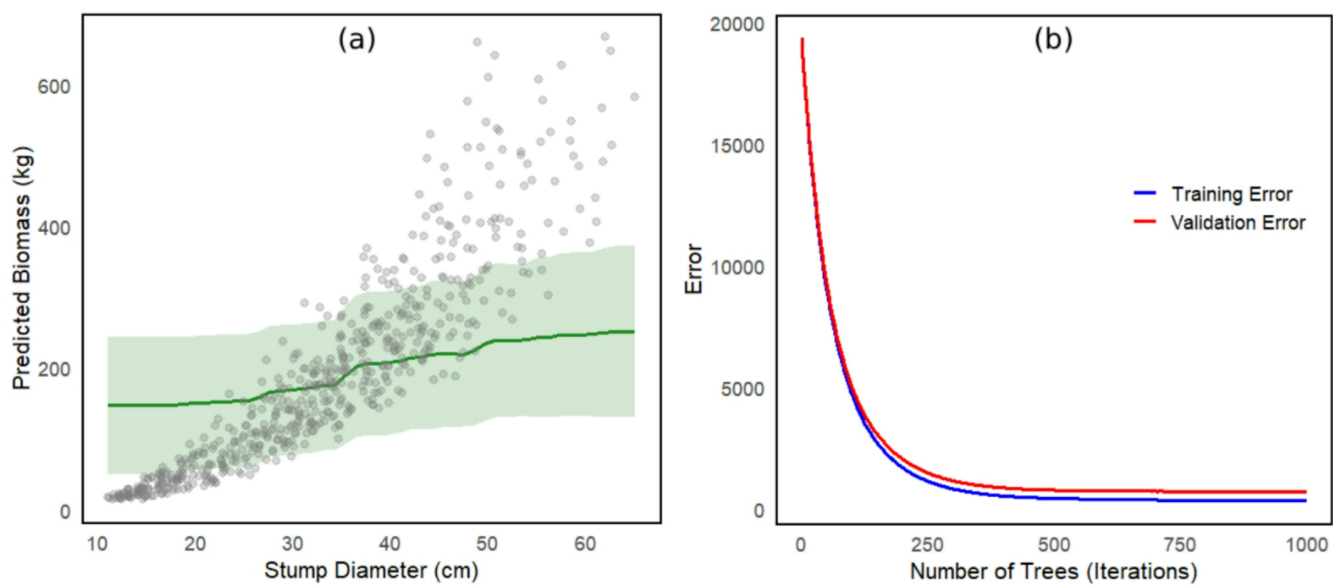


Figure 5

(a) Random Forest partial dependence plot showing the response of stem biomass to stump diameter with nonlinear increases in biomass; (b) Gradient Boosting learning curve (training versus validation error over iterations) emphasizing convergence and mild overfitting behavior

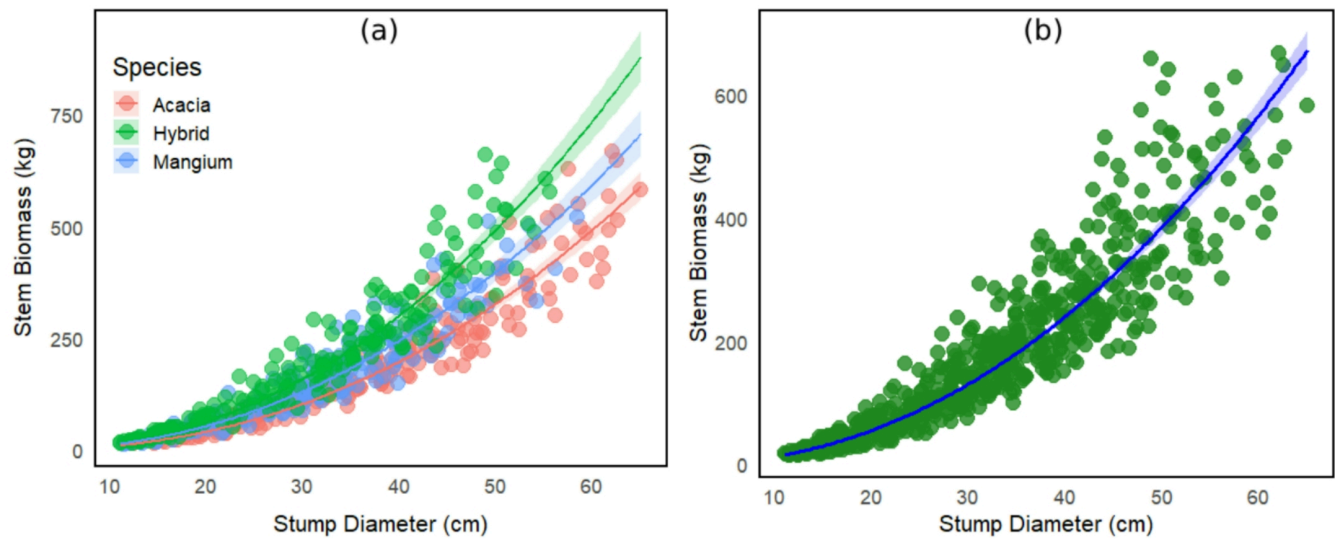


Figure 6

(a) Regression lines between stump diameter and stem biomass for *A. auriculiformis*, *A. mangium* and their hybrid showing species specific differences; (b) Combined regression fits (SB6 model) with confidence limits across all species showing adjusted $R^2 > 0.95$ confirming robustness of stump-based prediction

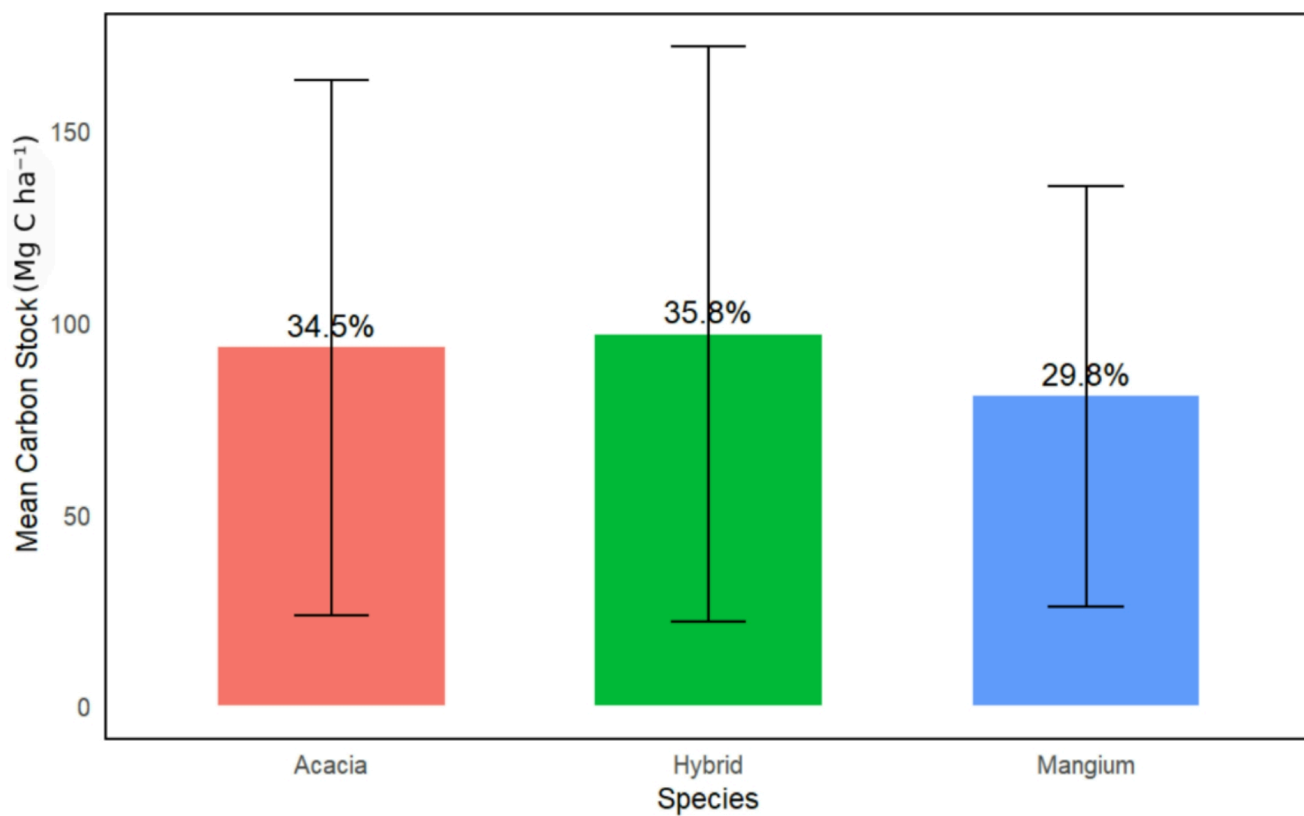


Figure 7

Carbon stock estimates (Mg C ha⁻¹) of *A. auriculiformis*, *A. mangium*, and hybrid Acacia, with error bars showing site variability

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryFile.docx](#)