

Article

Estimating Individual Leaf Area of *Dendrocalamus brandisii*: Allometric vs. Regression vs. Machine Learning

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Abstract

Accurate estimation of individual (culm-level) leaf area (LA) is essential to quantifying canopy structure, productivity, and carbon dynamics in bamboo plantations, yet it is often constrained by limited field data and high measurement costs. Using destructive sampling data from 52 *Dendrocalamus brandisii* culms in Sanya, China, we evaluated allometric models, regression approaches, and machine learning algorithms for estimating individual LA. Candidate models were built from diameter at breast height (DBH), culm height (H), and their combinations and were assessed via five-fold cross-validation, bootstrap uncertainty analysis, and the small-sample corrected Akaike Information Criterion (AICc). DBH was the dominant predictor of LA ($r = 0.826$), whereas adding H yielded no improvement due to strong collinearity ($r = 0.922$). The simple DBH-based power-law model ($LA = a \cdot DBH^b$, $b \approx 1.8$) achieved the best balance between accuracy and parsimony, explaining ~61% of the cross-validated variance with stable bootstrap parameters. Although Random Forest showed high in-sample fit ($R^2 = 0.942$), its cross-validated performance was low ($R^2 = 0.496$), indicating overfitting when using small samples. These results demonstrate that DBH-based allometric models provide a robust, interpretable, and cost-effective tool for large-scale biomass and carbon stock assessment in *D. brandisii* plantations.

Keywords: *Dendrocalamus brandisii*; bamboo plantations; leaf area estimation; DBH; allometric model; machine learning



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1. Introduction

Bamboo forests are becoming increasingly significant in subtropical and tropical ecosystems owing to their quick growth rate, high productivity, and substantial carbon sequestration potential [1–3]. A precise assessment of leaf area is essential to understanding canopy architecture, photosynthetic potential and ecosystem dynamics, including transpiration and carbon exchange [4–6]. Leaf area at individual culm level directly affects light interception and gas exchange capacity, and consequently growth rate and total productivity [7–9]. It is therefore very important to be able to accurately measure the total leaf area of each individual culm, which will allow the study of how biomass is distributed and how carbon moves through different forest systems.

It is important to measure the total leaf area of an individual bamboo plant, but it is very hard. The destructive sampling method needs a lot of labor and time; therefore, it is not suitable for large-scale inspections or repeated evaluations. Indirect estimation methods, such as allometric growth models, use easily measurable structural factors, such as stem diameter and total height, to estimate leaf area [10,11]. There are many growth equations available, which cover many different types of plants, but the unique modular culm structure and growth physiology of bamboo mean that new equations need to be established for different types of bamboo [12,13]. From a morphofunctional perspective, this structural and physiological uniqueness directly shapes the differential coupling between structural traits and individual leaf area. Unlike woody trees, where height growth, radial thickening and canopy development proceed synchronously, clumping bamboos complete full culm height elongation within a short period via intercalary meristem activity, with maximum height largely established before leaf expansion and canopy formation. As a result, culm height is determined primarily by internode number and elongation during the rapid growth stage and has only weak functional coupling with subsequent leaf area expansion. In contrast, diameter at breast height (DBH) is tightly linked to culm wall thickness, vascular bundle density and effective conduit cross-sectional area—traits that collectively set the upper limit of hydraulic transport capacity and mechanical support for the entire crown. For hollow bamboo culms in particular, load-bearing and hydraulic functions are concentrated in the culm wall, whose cross-sectional area scales reliably with DBH. This inherent functional constraint creates a far stronger allometric linkage between DBH and individual leaf area, meaning that culm height contributes limited independent explanatory power beyond the information already captured by DBH.

In recent years, machine learning algorithms have become increasingly popular, which provides a new method for ecological modeling based on a massive number of data. For bamboo systems in particular, this methodological development carries a distinct ecological relevance beyond a generic technical comparison. Classical allometric theory was largely developed and validated for solid-stem woody trees, whilst clumping bamboos feature unique biological traits such as clonal growth, hollow culm structure, and highly synchronized internode development, leaving the applicability of standard allometric scaling rules to bamboo stands needing further verification. A head-to-head comparison between theory-driven allometric models and data-driven machine learning methods would therefore also serve as an empirical test of whether universal plant structure–function scaling principles apply to bamboo, with its specialized growth strategy and hydraulic architecture. Machine learning algorithms, e.g., Random Forest and support vector machines, can capture complex non-linear relationships without the need to specify particular model forms and hence can improve prediction accuracy [14,15]. However, these methods typically require substantial training datasets to prevent overfitting, and they can be unstable when sample sizes are small, a common issue in ecological field studies [16,17]. There is thus a need for a critical comparison between traditional, theory-driven allometric growth models and flexible machine learning methods in order to determine the most robust and reliable approach for estimating the total leaf area of individual plants when data are limited.

Dendrocalamus brandisii (hereafter *D. brandisii*) is a large clumping species of bamboo, highly prized for its edible bamboo shoots and usable culms [18,19]. It is commonly grown in Yunnan and has been introduced into Hainan province of China. Accurately estimating the total leaf area of individual bamboo is crucial to optimizing the management of artificial bamboo forests, assessment of productivity, and study of carbon dynamics [10]. However, so far, no studies have systematically developed and validated a model for predicting the total leaf area of a single *D. brandisii* culm. There is particularly a lack of research on the performance of allometric and machine learning growth models in scenarios involving

small sample sizes. Such a comparison is needed, as most existing allometric equations for leaf area estimation have been developed and validated primarily for timber tree species, while empirical evidence for clumping bamboo species remains comparatively limited.

To fill the gap, we collected bamboo data from the cultivated *D. brandisii* bamboo forest in Sanya, Hainan Province, China. The core objectives of this study were three-fold: (1) to develop practical inventory estimation equations for total leaf area per individual of 2–3-year-old *D. brandisii*; (2) to systematically compare the estimation performance of three modeling paradigms, namely, allometric growth models, statistical regression models, and machine learning models, in a small-sample scenario; (3) to quantify the incremental information value of culm height for leaf area estimation beyond diameter at breast height (DBH). Furthermore, five-fold cross-validation, bootstrap resampling, and information-theoretic criteria were employed to evaluate the predictive accuracy, robustness, and parsimony of the models, and the uncertainty in parameter estimation was quantified.

2. Materials and Methods

2.1. Study Area

The research area was located in Sanya City, in the southwest of Hainan Province, China (Figure 1). Its coordinates range from east longitude $108^{\circ}56'$ to $109^{\circ}48'$ and from north latitude $18^{\circ}09'$ to $18^{\circ}37'$. This area is situated in the tropical region of China and has a tropical maritime monsoon climate. It has high humidity and moderate temperature, which is conducive to rapid bamboo culm growth and canopy development.

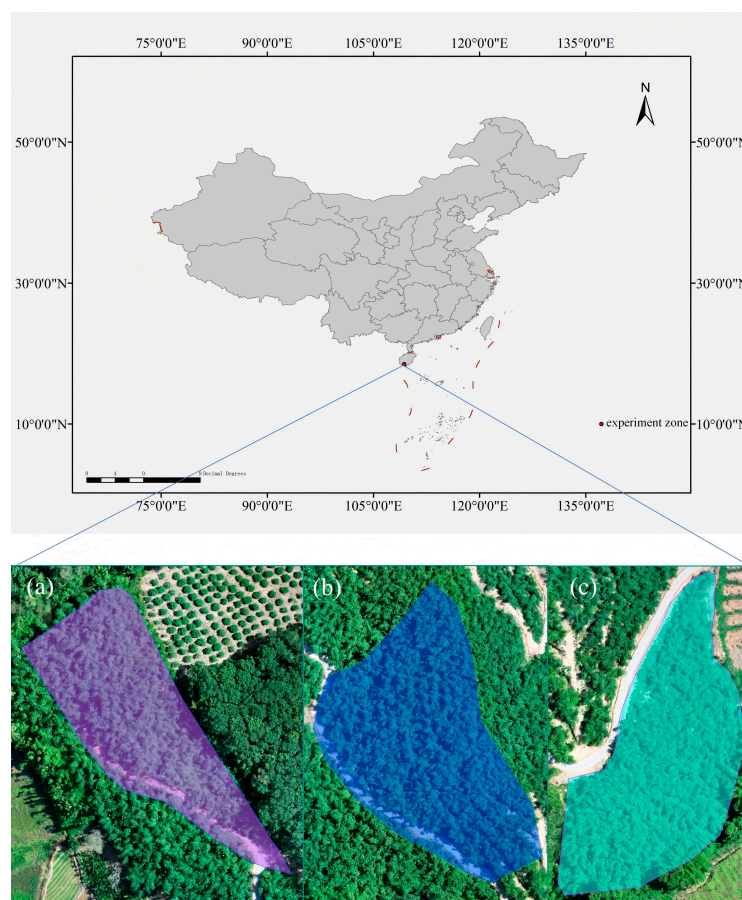


Figure 1. Locations of the representative sampling points of the study area. Plots (a–c) are highlighted in purple, blue, and green, respectively, representing three distinct experimental sites from which samples were collected.

The *D. brandisii* plantation was established in January 2021. Three representative sample plots with different slope aspects were established within the plantation; their spatial boundaries and topographic differences are shown in Figure 1a–c. All plots were planted with parent bamboos of the same age and had consistent afforestation and cultivation histories while varying in microtopographic characteristics. All culms sampled in this study were collected exclusively from this single plantation, with the three plots being selected to cover typical micro-site conditions across the stand.

2.2. Data Collection

The sampled culms were similar in age, mostly 2 to 3 years old, in the active growth period and functional maturity stage of *D. brandisii*. One-year-old culms were excluded from the analysis because their leaf growth was sparse or incomplete, which would have made it difficult to obtain accurate estimates of leaf area for each culm. Sampling was conducted in July 2023 and in March and August 2024. Sampling was stratified in all three sample plots to capture microtopographic variation within the plantation.

We used diameter-class (1 cm DBH) stratified sampling with a pre-survey of all three plots at the stand level for DBH. To avoid pseudoreplication due to genetic and micro-site correlation within clumps, only one standard culm was collected from each spatially separated bamboo clump. The sampling was proportional to the relative abundance of each diameter class, resulting in a final dataset of 52 independent individuals all sourced from the same plantation. The diameter at breast height (DBH) was measured with a diameter tape at 1.3 m above the ground [20]. The height of the culm (H) was measured using a calibrated measuring tape after each sampled culm was cut so that we could find the total length of the culm [21]. For *D. brandisii*, the diameter at breast height (DBH) remains quite stable after the culm matures. Consequently, the variation in DBH that was observed in this study was attributable to differences between different culms, rather than to differing growth stages of the culms.

We used destructive sampling and subsampling based on specific leaf area (SLA; cm^2/g) to determine the total leaf area (LA) of a single *D. brandisii* culm. All the leaves were collected after cutting each culm. The specific leaf area was measured on the batch and not on an individual basis. Prior to each destructive sampling batch, 200 leaf discs (6 mm in diameter) were punched from fully expanded, healthy leaves distributed across all individuals in that batch using a 6 mm diameter leaf punch, yielding a pooled sample representative of the batch. These discs were oven-dried at 65°C to constant mass using an electric blast drying oven (Model 101-3B, SUNNE, Shanghai Shangpu Instrument Equipment Co., Ltd., Shanghai, China) for the calculation of SLA. All remaining leaves from each culm were also oven-dried at 65°C to determine total leaf dry mass. Total leaf area per culm was derived by multiplying the corresponding batch SLA value by the total leaf dry mass of the culm [22–24]. Across the three sampling batches, the SLA values were 227.35, 196.19 and $286.65 \text{ cm}^2/\text{g}$, with an overall mean of $236.73 \text{ cm}^2/\text{g}$ and a coefficient of variation of 19.41%.

Total leaf area at the culm scale (LA) is given by Equation (1).

$$LA = SLA \cdot M_t \quad (1)$$

where $SLA = A_s/M_s$, A_s is the total area of the 200 leaf discs in the batch subsample, M_s is the corresponding dry mass of the batch subsample, and M_t is the total leaf dry mass of all leaves from the same culm.

SLA was determined for each sampling batch using the pooled disc subsample and was applied uniformly to all individuals within the same batch for leaf area upscaling.

Extreme outliers in the dataset were identified and excluded via the interquartile range (IQR) method during data preprocessing in order to guarantee data quality and mitigate the interference of abnormal observations on subsequent model fitting.

2.3. Model Construction

Three categories of models were developed to estimate the total leaf area (LA) of individual *D. brandisii* and evaluate the performance of various modeling approaches: (i) allometric models based on established scaling relationships, (ii) linear and log-linear regression models used as statistical benchmarks, and (iii) machine learning models focusing on predictive performance.

2.3.1. Allometric Models

Allometric models were developed under the assumption that leaf area scales with plant size following power-law relationships. We used diameter at breast height (DBH) and culm height (H) as predictor variables because they are commonly measured in bamboo forest inventories and are important structural features of individual culms [25,26].

Although inherent structural collinearity exists between DBH and culm height, we established both DBH-only univariate models and DBH + H bivariate models for two explicit research purposes. First, the bivariate model setting enables quantification of the incremental information value of culm height for leaf area estimation beyond DBH, responding to the common practical question of whether dual-factor models provide additional estimation gains in bamboo forest inventory. Secondly, it provides directly referable model forms for stand inventory practice and enables the testing of the applicability of common dual-factor allometric equations in *D. brandisii* stands.

Using non-linear least squares regression, we estimated the parameters of three commonly used allometric equations:

Model A (DBH-based power model):

$$LA = a \cdot DBH^b \quad (2)$$

Model B (DBH-H extended model):

$$LA = a \cdot DBH^b \cdot H^c \quad (3)$$

Model C (compound structural variable model):

$$LA = a \cdot (DBH^2 \cdot H)^b \quad (4)$$

2.3.2. Linear and Log-Linear Regression Models

We used the same variable scheme as the allometric models to create linear and log-linear regression models for comparison to non-linear allometric models. Logarithmic transformation linearizes power-law relationships and stabilizes variance. These regression models were included primarily as statistical references rather than as mechanistic representations of bamboo growth.

The multiple linear regression model was expressed as:

$$LA = a + b \cdot DBH + c \cdot H \quad (5)$$

The log-linear model was obtained by applying natural logarithmic transformation to both the response variable and predictors:

$$\ln(LA) = a + b \cdot \ln(DBH) + c \cdot \ln(H) \quad (6)$$

Direct exponentiation of predicted values from Equation (6) would introduce systematic re-transformation bias, so the Baskerville correction factor $CF = \exp(SEE^2 / 2)$ was multiplied to the back-transformed results to eliminate underestimation [27], where SEE denotes the standard error of estimate of the log-linear regression model.

2.3.3. Machine Learning Models

We used two popular machine learning algorithms, Random Forest (RF) regression and Support Vector Regression (SVR), to obtain more accurate predictions. The RF model is a kind of ensemble learning that makes many regression trees using bootstrap samples and random groups of predictor variables [28,29]. SVR employs kernel-based learning to ascertain the non-linear relationships between predictors and response variables [30,31]. Both RF and SVR models used diameter at breast height (DBH) and culm height (H) as predictor variables to ensure comparability with the regression-based approaches. Model hyperparameters were optimized using cross-validation to improve predictive performance and generalization ability.

2.4. Model Evaluation and Validation

All candidate models were first fitted to the complete dataset to obtain final parameter estimates and in-sample fit statistics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), Akaike Information Criterion (AIC), and the small-sample corrected AIC (AICc). The AICc was used to compare model parsimony and assist in selecting the optimal model.

We used 5-fold cross-validation to test predictive performance. This meant that the dataset was randomly split into five groups of about the same size. One of the subsets was used as validation data, and the other subsets were used to train the model in each iteration, until all subsets had served once as the validation set [32,33].

We performed non-parametric bootstrap resampling (1000 iterations, with replacement) to assess model stability under limited sample size. Bootstrap distributions were used to estimate model parameters (a, b, and c), prediction errors, and their 95% confidence intervals; parameter estimates are reported as bootstrap means. Table S1 (Supplementary Material) shows the parameter estimates that were found by fitting the full dataset to all candidate allometric models.

Residual diagnostics were also examined to assess whether there was any systematic bias across the fitted range. As no independent external validation dataset was available, model validation in this study should be regarded as internal validation based on cross-validation and bootstrap resampling.

The evaluation metrics were calculated as follows:

1. Coefficient of determination (R-squared, R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (7)$$

where:

y_i denotes the observed values.

$\hat{y}_i$ denotes the predicted values.

$\bar{y}$ is the mean of the observed values.

2. Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

where:

y_i denotes the observed values.

$\hat{y}_i$ denotes the predicted values.

n is the sample size.

3. Akaike Information Criterion Corrected (AICc):

$$AIC = 2k + n \left[\ln 2\pi \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} + 1 \right] \quad (9)$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \quad (10)$$

where:

k is the number of parameters.

n is the sample size.

y_i is the observed value.

$\hat{y}_i$ is the predicted value.

3. Results

3.1. Descriptive Statistics and Correlation Structure

The data for diameter at breast height (DBH), culm height (H), age, and individual leaf area (LA) for *D. brandisii* are summarized in Table 1.

Table 1. Descriptive statistics of structural variables and leaf area.

	Count	Mean	Std	Min	Max	CV (%)
DBH (cm)	52	4.558	1.796	1.600	8.360	39.392
Height (m)	52	8.027	3.249	2.800	16.300	40.472
Age (yr)	52	2.500	0.505	2.00	3.00	20.195
Leaf Area (m ²)	52	12.554	9.561	0.960	40.230	76.159

DBH varied from 1.600 to 8.360 cm, with an average of 4.558 cm (SD = 1.796 cm). The culm height varied between 2.80 and 16.30 m, with an average of 8.027 m (SD = 3.249 m). The total leaf area per plant varied greatly, from 0.960 to 40.230 m², with an average of 12.554 ± 9.561 m². The coefficient of variation for total leaf area (76.16%) was much higher than for DBH (39.392%) or culm height (40.472%). This pronounced variation in leaf area may stem from multiple combined factors. It partly reflects differences in foliar allocation among culms of similar structural size and may also be driven by sampling noise, seasonal variation across collection dates, accumulated error in SLA-based estimation, and unmeasured microenvironmental heterogeneity.

The results of the Pearson correlation analyses indicated robust positive correlations between LA and DBH ($r = 0.826$, $p < 0.01$) and between LA and height (H) ($r = 0.760$, $p < 0.01$). However, LA showed a negative relationship with age ($r = -0.701$, $p < 0.01$). DBH and H were very closely related ($r = 0.922$, $p < 0.01$), which means that the structural predictors might be multicollinear (see Table 2).

We calculated variance inflation factors (VIFs) to look more closely at possible multicollinearity among the predictors. VIF diagnostics indicated moderate multicollinearity for DBH (VIF = 8.523) and height (VIF = 6.713), whereas age exhibited no significant collinearity concerns (VIF = 3.374) (see Figure 2).

Table 2. Pearson correlation coefficients among individual growth traits of *D. brandisii*.

	DBH (cm)	Height (m)	Age (yr)	Leaf Area (m ²)
DBH (cm)	1			
Height (m)	0.922 **	1		
Age (yr)	−0.838 **	−0.788 **	1	
Leaf Area (m ²)	0.826 **	0.760 **	−0.701 **	1

Note: ** $p < 0.01$.

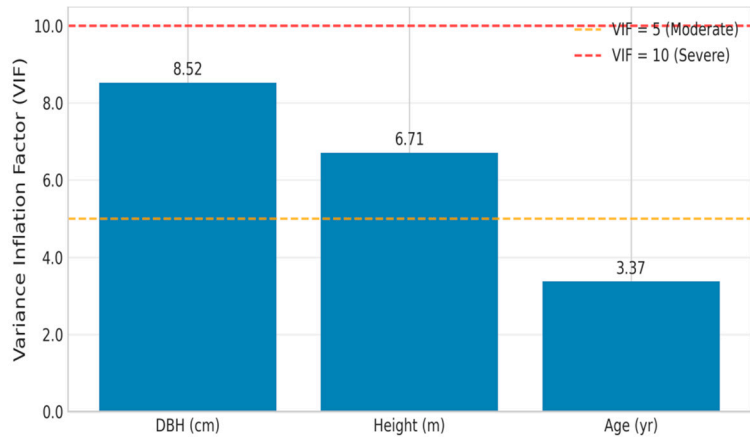


Figure 2. Variance inflation factors analysis of candidate predictors.

3.2. Model Performance Comparison

The performance of the models is detailed in Table 3. Allometric models consistently demonstrated strong and stable predictive performance across all assessed methodologies, especially the model relying exclusively on DBH. Model A was the best-performing of all the allometric formulations tested. It had the lowest AICc value (173.760) and achieved the optimal balance between goodness-of-fit and model parsimony. Models with more predictors (e.g., culm height, Model B) or different structural expressions (Model C) resulted in higher RMSE and AICc. These models also performed less well on cross-validation, with lower CV-R² and higher CV-RMSE. Therefore, increasing the model complexity does not improve their performance. Moderate predictive accuracy was observed with linear and log-linear regression models. The log-linear model was better than the simple linear model, but both were still worse than the best allometric model. The machine learning approaches showed different performance levels. Although the Random Forest model had the highest apparent calibration fit (R² = 0.942), this advantage was not observed under cross-validation (CV-R² = 0.496; CV-RMSE = 5.659 m²), which suggests limited generalizability and likely overfitting under the small-sample condition. Support vector regression (SVR) was similarly unstable across validation folds.

Table 3. Model performance comparison (R², RMSE, AICc, and cross-validation results).

Model	R ²	RMSE (m ²)	CV-R ²	CV-RMSE (m ²)	AICc
Model A	0.710	5.104	0.609 ± 0.230	5.058 ± 2.066	173.760
Model B	0.713	5.073	0.582 ± 0.217	5.290 ± 2.111	175.393
Model C	0.678	5.373	0.584 ± 0.249	5.244 ± 2.315	179.109
Linear regression	0.682	5.340	0.536 ± 0.253	5.534 ± 2.263	180.721
Log-linear regression	0.695	5.229	0.569 ± 0.264	5.295 ± 2.234	178.546
Support Vector Regression	0.669	5.444	0.495 ± 0.290	5.973 ± 2.920	182.726
Random Forest	0.942	2.288	0.496 ± 0.323	5.659 ± 2.327	-

Note: The AICc is not reported for the Random Forest model because this is a non-parametric ensemble method which does not provide a likelihood function.

To further assess the reliability of the predictions at an individual level, 95% prediction intervals and their empirical coverage were calculated for all candidate models (Table 4). Empirical coverage of the three allometric models and the linear regression model was 0.942, which was near the nominal 95% level and confirmed well-calibrated interval estimation. Among them, Model A had the lowest mean prediction interval (21.303 m²), indicating the lowest individual prediction uncertainty, and the models with height (Model B: 21.587 m²; Model C: 22.427 m²) resulted in slightly wider intervals, further confirming the finding that the inclusion of culm height did not reduce prediction uncertainty. The log-linear model had slightly conservative coverage (0.962) but the widest mean interval (29.504 m²). Its maximum upper bound was 92.758 m², indicating a marked inflation of prediction uncertainty in the high-DBH range after logarithmic back-transformation. Note that although SVR and RF obtained the narrowest nominal intervals (mean widths of 7.436 m² and 8.499 m², respectively), their empirical coverage values were only 0.442 and 0.596, well below the nominal 95% level. Thus, their apparently precise intervals greatly underestimated the true prediction uncertainty, adding to the evidence for overfitting in the small-sample condition. Together, these results confirmed the parsimonious DBH-based Model A as the most reliable and well-calibrated predictive performance.

Table 4. Summary statistics with 95% prediction intervals and empirical coverage for all candidate models.

Model	Mean_PI_Width	Median_PI_Width	Minimum_PI_Lower	Maximum_PI_Upper	Empirical_Coverage
Model A	21.303	21.210	−8.773	44.945	0.942
Model B	21.587	21.332	−8.962	44.523	0.942
Model C	22.427	22.314	−8.841	46.320	0.942
Linear regression	22.731	22.559	−11.915	41.075	0.942
Log-linear regression	29.504	24.765	0.761	92.758	0.962
Support Vector Regression	7.436	7.098	1.154	31.265	0.442
Random Forest	8.499	6.015	0.967	39.690	0.596

Note: All prediction intervals (PIs) are reported at the 95% level. Empirical coverage denotes the proportion of observed leaf area values falling within the nominal 95% prediction interval; a value close to 0.95 indicates well-calibrated interval estimation.

We also conducted a prediction sensitivity analysis at the 5th and 95th percentiles of the sampled DBH distribution to further evaluate structural extrapolation risk beyond global prediction interval statistics (Table 5). This covered the main body of the data while excluding extreme outlier values. Relative prediction sensitivity was identical at both boundaries for all allometric power-law models but absolute prediction deviation was much higher at the upper DBH boundary, suggesting greater uncertainty for large-diameter individuals. The linear regression model showed extreme instability at the lower DBH end with a relative change of more than 260%, further confirming the advantage of allometric equations in leaf area estimation. We recommend caution in the use of the models near the boundaries of the sampled DBH range and advise against extrapolation outside the range of the observed data distribution.

Figure 3 shows the observed vs. predicted LA values for all models. Allometric models based on DBH predicted values very close to the 1:1 line (the red dashed line) and more complex models (e.g., linear regression, log-linear regression, and SVR) showed greater scatter, particularly at higher LA values. The cross-validation results in Figure 4 support this visual pattern, with the parsimonious allometric models showing lower variability and therefore more stable and consistent performance than more complex models.

Table 5. Prediction sensitivity analysis at the lower and upper boundaries of the sampled DBH range.

Model	Lower DBH Boundary (1.81 cm)			Upper DBH Boundary (7.501 cm)		
	Baseline LA (m ²)	Max Absolute Change (m ²)	Max Relative Change (%)	Baseline LA (m ²)	Max Absolute Change (m ²)	Max Relative Change (%)
Model A	2.152	0.4	18.61	27.45	5.109	18.61
Model B	1.674	0.361	21.54	30.724	6.618	21.54
Model C	4.162	0.466	11.2	20.276	2.271	11.2
Linear regression	0.309	0.806	261.22	25.666	3.342	13.02
Log-linear regression	3.208	0.462	14.41	23.896	3.443	14.41

Note: Boundary sensitivity analysis was conducted at the 5th percentile (1.81 cm) and 95th percentile (7.50 cm) of the observed DBH distribution, in the mean culm height scenario (8.027 m). At each boundary point, DBH was perturbed by $\pm 5\%$ and $\pm 10\%$, and predicted leaf area was recalculated for each model. Baseline LA refers to the predicted value at the unperturbed boundary DBH. Local elasticity denotes the proportional response of predicted LA to proportional DBH change. Max Absolute Change and Max Relative Change (%) represent the maximum deviation of predicted LA induced by DBH perturbation at each boundary, quantifying prediction sensitivity and extrapolation risk near the edges of the main data distribution.

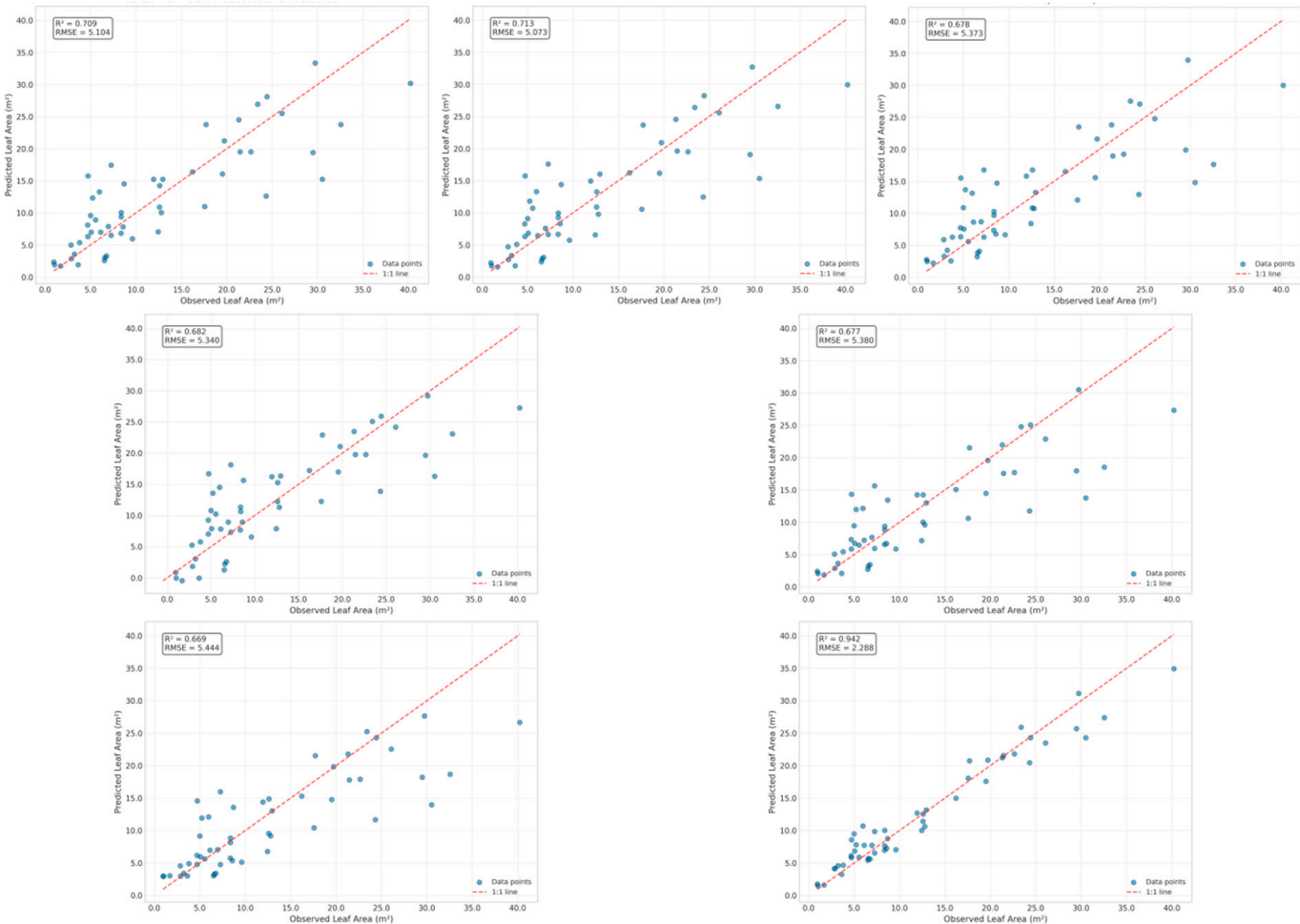


Figure 3. Observed versus predicted individual leaf area (LA) for all seven candidate models, grouped by category: allometric models in the first row, classical regression models (linear and log-linear) in the second row, and machine learning models (SVR and Random Forest) in the third row. Blue dots denote individual observations; the red dashed line indicates the 1:1 reference line. R^2 and RMSE are annotated in each panel.

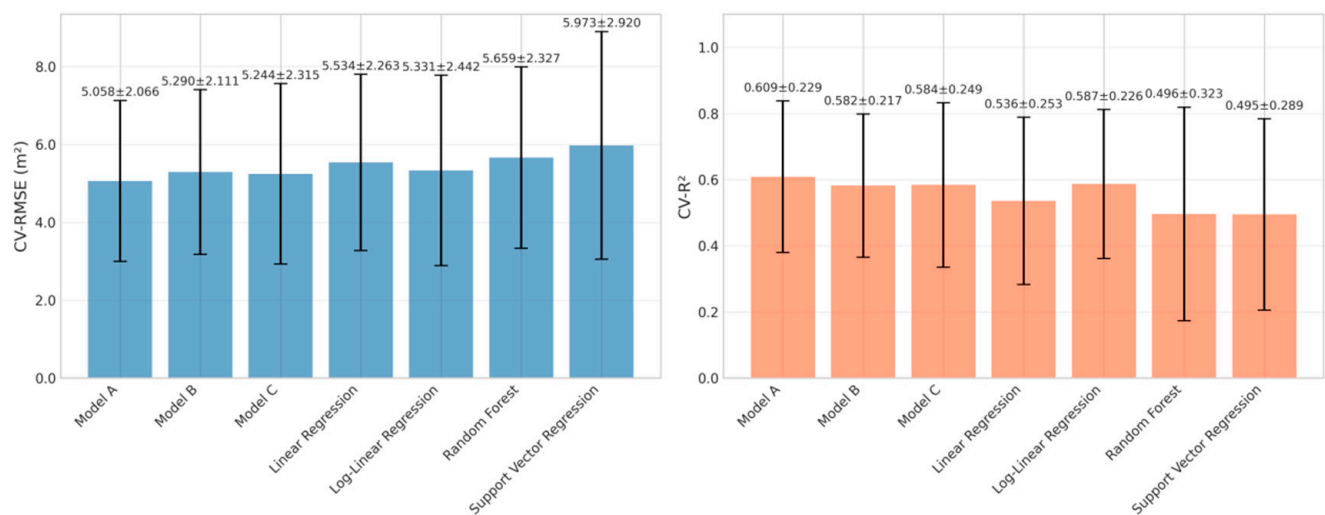


Figure 4. Cross-validation results (RMSE and R^2 across folds).

3.3. Parameter Sensitivity and Structural Dominance

Sensitivity analysis of the allometric parameters showed that the culm diameter was significantly correlated with variation in total leaf area. The scaling exponent b in the DBH-based power-law model (Model A) was always >1 , with a bootstrap mean of about 1.80, with confidence intervals not too wide (Table 6). In Model B (the DBH–H model), the mean predicted exponent for culm height (c) was -0.090 , with a 95% confidence interval from -0.657 to 0.959 . This shows that there was considerable uncertainty and that height had a weak effect. Model C also had fairly stable parameter estimates, but its composite structure made it difficult to interpret the effects of each variable directly.

Table 6. Allometric model parameters and bootstrap confidence intervals.

Model	a	b	c	a (95% CI)	b (95% CI)	c (95% CI)
A	0.765	1.813	–	0.301–1.372	1.475–2.285	–
B	0.812	1.901	-0.090	0.287–1.610	0.674–2.653	$-0.657-0.959$
C	0.680	0.566	–	0.291–1.173	0.468–0.698	–

Note: The parameter estimates (a , b , and c) are presented as bootstrap means obtained from the nonparametric resampling of the original dataset. We used 1000 bootstrap iterations to measure uncertainty and the percentile method to find 95% confidence intervals. Dashes indicate that the parameters are not included in the model.

Residual diagnostics (Figure 5) further corroborated these patterns. Residuals (the difference between observed and predicted values) were mostly close to zero for all models. For the DBH-based allometric models (Models A, B, and C) and the linear regression model, the residual trend lines stayed mostly horizontal across the fitted range, with no clear systematic bias. On the other hand, models like Random Forest, Support Vector Regression, and log-linear regression had more variable residuals and less consistent patterns across the fitted range.

When examined together, these results show that culm diameter is the main factor that explains changes in total leaf area.

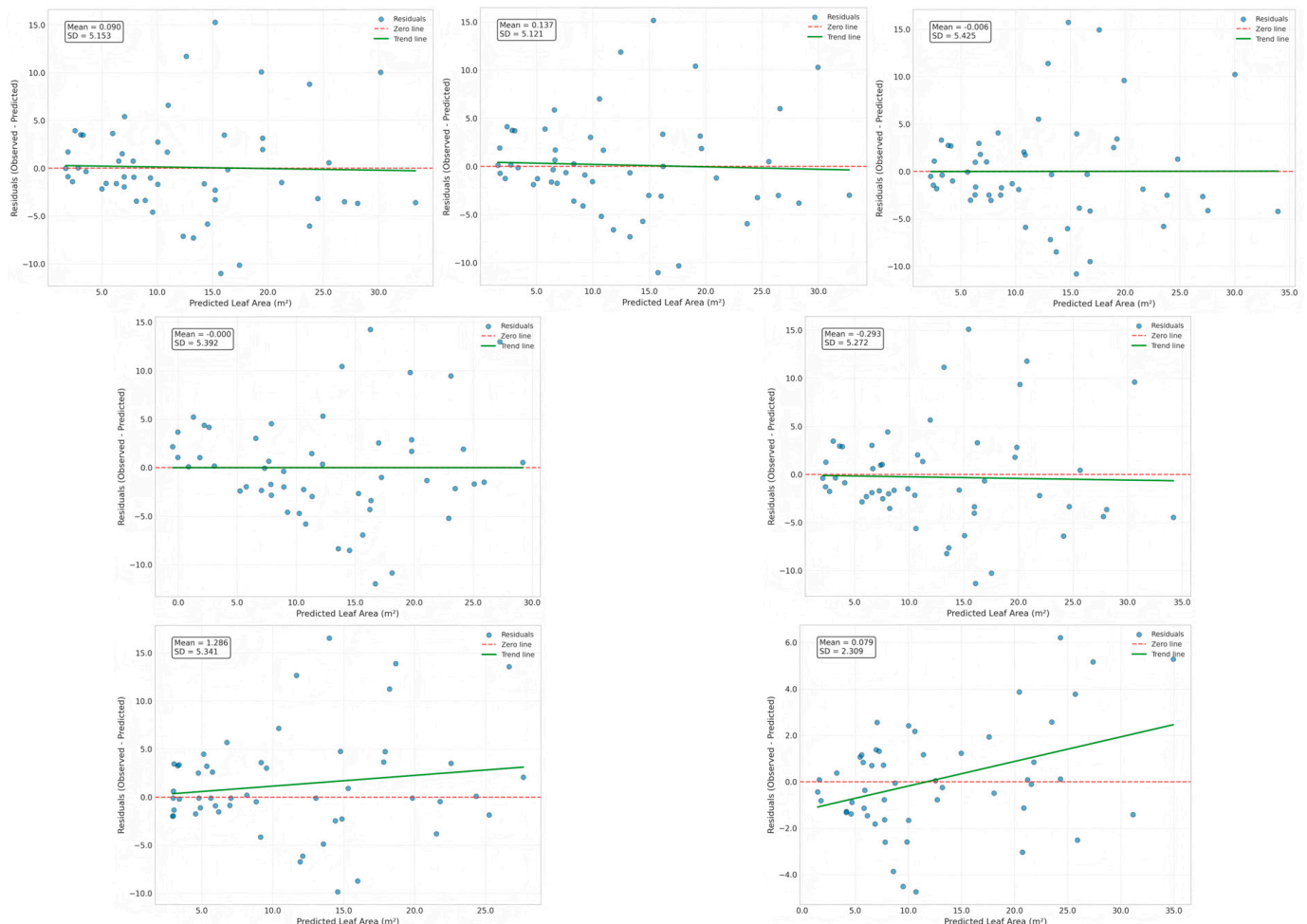


Figure 5. Residual analysis (observed–predicted LA versus predicted LA) for all seven candidate models, grouped by category: allometric models in the first row, classical regression models (linear and log-linear) in the second row, and machine learning models (SVR and Random Forest) in the third row. Blue dots denote residuals; the red dashed line indicates zero residual, and the green solid line represents the residual trend. Mean residual and SD are annotated in each panel.

4. Discussion

4.1. DBH Dominance and the Limited Incremental Value of Culm Height

We have demonstrated that diameter at breast height (DBH) is the primary structural variable that can be used when determining individual total leaf area (LA) in *D. brandisii*. Across all candidate models, DBH-based allometric formulations consistently achieved superior overall performance in terms of prediction accuracy, parameter stability, and model parsimony compared with formulations that explicitly incorporated culm height (H) [34,35]. This result confirms that DBH is the most important structural factor explaining total leaf area (LA) of *D. brandisii* in the studied population.

These results are consistent with general plant allometric theory that predicts that diameter-related traits capture the major dimensions of plant hydraulic transport capacity, mechanical support, and carbon transport potential and thus provide a critical nexus linking plant structural traits with functional performance [36–38]. In bamboo culms, DBH directly constrains the density of vascular bundles and the effective cross-sectional area of conductive tissues, and this is the main constraint on maximum hydraulic conductivity and thus the maximum transpiring leaf area that can be supported at the individual level [39–41]. Within the age range examined in this study, the structural load-bearing

and resource transport capacity represented by DBH exhibited a stronger and more stable association with LA accumulation than culm height [42,43].

The bivariate analysis showed a strong correlation between individual LA and culm height. However, the inclusion of height in the allometric models only slightly improved their performance and made parameters much less certain [25,44]. Scaling exponents related to height were weak and unstable across sample iterations in bootstrap resampling [45]. This means that culm height contributed little independent information to explain individual LA variation after accounting for DBH, which is consistent with well-documented allometric covariation among plant size traits [46,47]. The instability of height-related parameters was further demonstrated by the negative point estimate of the height exponent in Model B ($c = -0.09$; Table 4), whose confidence interval included zero. This pattern should be primarily interpreted as a symptom of parameter non-identifiability induced by strong multicollinearity between DBH and culm height, rather than a direct reflection of weak or negative biological influence of height on leaf area. When two structurally coupled size traits share a large proportion of their covariation with leaf area, the model cannot uniquely disentangle their independent functional contributions from the available data, leading to highly volatile coefficient estimates and spurious sign shifts. At the model level, this means that the inclusion of height as a second predictor does not translate to meaningful gains in predictive accuracy but rather reduces parameter stability and model generalizability. Hence, this provides a key statistical justification for the adoption of the parsimonious DBH-only allometric model.

From a biological point of view, this statistical pattern has a clear developmental basis. Culm height is mainly determined during a short period of rapid elongation by intercalary meristems, while radial growth better represents later structural reinforcement and resource allocation capacity [48,49]. Previous studies have shown that Moso bamboo (*Phyllostachys edulis*) does not produce leaves until it reaches a certain height and that there is a weak direct correlation between culm height and leaf development [50]. Similar patterns have been widely reported in allometric studies of other species of bamboo and woody plants. Height usually adds little to the explanation at the level of the individual plant [51,52].

The strong collinearity that we found between DBH and culm height limits the practical value of adding height as a predictor for estimating leaf area at the individual level [53]. Importantly, this statistical redundancy does not detract from the intrinsic biological value of culm height, which performs critical functions in light interception, the positioning of the canopy and mechanical support, but rather reflects the fact that its independent effect could not be disentangled due to close structural coupling to DBH during culm development. Conversely, parsimonious allometric models based on DBH can effectively reduce parameter redundancy while maintaining predictive accuracy, making them more robust and interpretable [54]. Destructive sampling for the measurement of total leaf area in bamboo forests is often a costly and labor-intensive task. DBH is a simple-to-measure, rapid and non-destructive structural trait that allows for the determination of the individual total leaf area [55–57].

4.2. Implications of the Comparison Between Allometric and Machine Learning Approaches

We compared the performance of biologically grounded allometric models and data-driven machine learning approaches for predicting the total leaf area of individuals. An important finding is that increased model flexibility does not result in better predictive generalization, given the limited sample size and the limited set of predictors used in this study.

The Random Forest model showed excellent goodness-of-fit in sample-based calibration, but its performance degraded substantially in cross-validation, indicating a higher risk of overfitting with small sample sizes [58,59]. The Support Vector Regression model showed variable performance during cross-validation, reflecting generalization challenges faced by high-flexibility models for the data size and predictor configuration of the current study [60,61].

Importantly, all machine learning models were implemented with predefined hyperparameters, rather than being tuned extensively. Therefore, the observed instability was likely due to the intrinsic sensitivity of flexible algorithms to small sample sizes rather than a tuning-induced bias. The distinction suggests that the weaker generalization of machine learning models that we identified in this study was due to insufficient sample support for complex functional forms, not to flaws in model implementation.

In contrast, allometric models based on biological scaling theory demonstrated superior generalization ability and more stable parameter estimates. DBH-based allometric models consistently outperformed other modeling frameworks in terms of prediction accuracy, parameter stability, and model parsimony when compared with formulations that explicitly took into account culm height (H) [62,63]. DBH provides a central structural constraint to bamboo leaf area estimation, leading to a strong, inherently stable allometric relationship, with little systematic residual variation to be exploited by flexible data-driven models. Under these conditions, increasing model complexity in the absence of biological constraints mainly captures sampling noise rather than true functional relationships. This may explain why we did not find the accuracy improvements often reported for machine learning approaches applied to larger and more heterogeneous datasets. This finding is consistent with a view gaining traction among many ecologists, namely, that the application of machine learning algorithms directly on insufficiently large datasets often fails to produce robust and interpretable results [64,65].

Our results indicate that in bamboo research, where destructive sampling restricts the number of data that can be obtained and the structural uniformity of culms is consistent with assumptions of biological scaling, theory-based allometric methods are preferable to data-hungry machine learning algorithms for estimating leaf area and operational forest inventories [10,25,47].

4.3. Limitations and Scope of Application

Several limitations should be acknowledged when interpreting our findings, as they define the boundary conditions and generalizability of the proposed allometric models.

First, all the *D. brandisii* culms that were sampled lay within a narrow age range of 2–3 years. Thus, the leaf area estimation equations and the related conclusions obtained in this study are currently only valid for 2–3-year-old individuals. Furthermore, stand structural traits and environmental factors such as stand density, intra-clump competition, soil fertility, and water availability were not explicitly included in the modeling framework. DBH development and culm developmental pathways are influenced by these factors, which can indirectly limit leaf area expression [66–68]. The observed dominant DBH–LA relationship, with its strong power-law pattern and consistent allometric exponent, should be interpreted as site- and age-specific outcomes, rather than invariant species-level scaling laws, given the narrow range of stand environments included in the dataset. Also, while we sampled during several seasons, we did not explicitly measure the degree of seasonal variation in individual leaf area. Changes in phenology of leaf retention and canopy turnover can influence total leaf area through the annual cycle, and this may introduce additional uncertainty into estimated allometric relationships.

Second, there are several methodological limitations that could affect the reliability of the model. These models were only internally validated using cross-validation and bootstrap resampling, and no independent external dataset was used to evaluate the model. However, extrapolation beyond the observed range of DBH is inherently risky because the relatively small sample size causes allometric fits to differ from the expected pattern at the lower and upper limits of the predictor variable. Power-law models showed scale-invariant relative sensitivity, but the absolute deviation in predictions increased substantially towards the upper boundary (0.400 m² to 5.109 m² for Model A), indicating substantially larger absolute uncertainty for large-diameter individuals. As we measured the total leaf dry mass per culm but not the total leaf area, the total leaf area was estimated by multiplying the total leaf dry mass by the SLA measured at the batch level. However, SLA varied substantially seasonally, from 196.19 to 286.65 cm²/g (CV = 19.41%) among batches, resulting in systematic uncertainty in LA estimates at the batch level. The variability of this SLA and the low number of sampled batches do not allow for a full characterization of the SLA temporal dynamics. Future studies with a larger number of sampling batches and measurements of SLA at the individual level would further improve the accuracy of leaf area estimation.

Nevertheless, this study still contributes to filling a significant regional research gap. Most existing leaf area allometric equations have been developed and validated mainly for timber tree species, while empirical evidence for sympodial clumping bamboos is still relatively scarce. *D. brandisii* is a typical clumping bamboo and is quite different from arborescent trees in culm structure, dynamics of canopy development and biomass allocation strategies. In addition, the studied population was introduced to the tropical region of Sanya, Hainan, where unique hydrothermal conditions shape distinct growth traits relative to its native range. To date, no site-specific leaf area allometric model has been reported for this introduced bamboo population under such environmental contexts. The species and site-specific parameters presented here provide direct empirical support for the management of local bamboo forest, canopy functional monitoring and carbon sink assessment, while enriching the basic allometric dataset for clumping bamboo taxa for future cross-species comparative studies. In the future, it will be important to conduct research that incorporates broader age gradients, density-dependent effects, environmental covariates and continuous fixed-point observations throughout the year to determine the regulatory mechanisms of age class, seasonality and environmental heterogeneity on individual leaf area and to further improve the universality and reliability of DBH-based leaf area estimation models.

5. Conclusions

In this study, we evaluated various allometric and data-driven models to estimate the total leaf area of individual culms of *D. brandisii* using easily measurable structural variables. DBH was consistently the most important factor to predict the total leaf area of each individual in all candidate models, and the addition of culm height (H) only marginally improved the fitting performance. Thus, structural aspects associated with diameter are the major determinants of the total leaf area per individual culm. Basic DBH-based power-law allometric models were as good as more complex models and machine learning approaches for prediction but were simpler, more stable and easier to understand. The strong overfitting of Random Forest models is a warning about the dangers of applying data-hungry methods to ecological data with small sample sizes. Our results indicate that DBH-based allometric models can be used to estimate the total leaf area of a single *D. brandisii* culm in the setting of the studied plantation, which has obvious implications for the refined and precision management of *D. brandisii* plantations. The proposed models were

developed and validated for the specific environmental conditions, plantation management regimes and age range of the study site, and their use should be limited to similar site conditions and culm age classes. Extrapolation of these models to other geographic regions, different soil or climate conditions or bamboo plantations with substantially different stand characteristics should be made cautiously and requires further local calibration.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f17080863/s1>, Table S1. Parameter estimates for all candidate allometric models.

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References

1. Yuen, J.; Fung, T.; Ziegler, A. Carbon stocks in bamboo ecosystems worldwide: Estimates and uncertainties. *For. Ecol. Manag.* **2017**, *393*, 113–138. [[CrossRef](#)]
2. Zhou, X.; Zhou, Y.; Zhang, X.; Sharma, R.P.; Guan, F.; Fan, S.; Liu, G. Two-level mixed-effects height to crown base model for moso bamboo (*Phyllostachys edulis*) in Eastern China. *Front. Plant Sci.* **2023**, *14*, 1095126. [[CrossRef](#)] [[PubMed](#)]
3. Kongjarat, W.; Han, L.; Aritsara, A.N.A.; Zhang, S.-B.; Zhao, G.-J.; Zhang, Y.-J.; Maenpuen, P.; Li, Y.-M.; Zou, Y.-K.; Li, M.-Y.; et al. Hydraulic properties and drought response of a tropical bamboo (*Cephalostachyum pergracile*). *Plant Divers.* **2024**, *46*, 406–415. [[CrossRef](#)] [[PubMed](#)]
4. Street, L.; Shaver, G.; Williams, M.; Wijk, M. What is the relationship between changes in canopy leaf area and changes in photosynthetic CO₂ flux in arctic ecosystems? *J. Ecol.* **2007**, *95*, 139–150. [[CrossRef](#)]
5. Kamoske, A.; Dahlin, K.; Stark, S.; Serbin, S. Leaf area density from airborne LiDAR: Comparing sensors and resolutions in a temperate broadleaf forest ecosystem. *For. Ecol. Manag.* **2019**, *433*, 364–375. [[CrossRef](#)]
6. Zhu, Y.; Li, D.; Fan, J.; Zhang, H.; Eichhorn, M.P.; Wang, X.; Yun, T. A reinterpretation of the gap fraction of tree crowns from the perspectives of computer graphics and porous media theory. *Front. Plant Sci.* **2023**, *14*, 1109443. [[CrossRef](#)] [[PubMed](#)]
7. Weraduwege, S.; Chen, J.; Anozie, F.; Morales, A.; Weise, S.; Sharkey, T. The relationship between leaf area growth and biomass accumulation in *Arabidopsis thaliana*. *Front. Plant Sci.* **2015**, *6*, 167. [[CrossRef](#)] [[PubMed](#)]
8. Kong, Y.; Nemali, K. Blue and Far-Red Light Affect Area and Number of Individual Leaves to Influence Vegetative Growth and Pigment Synthesis in Lettuce. *Front. Plant Sci.* **2021**, *12*, 667407. [[CrossRef](#)] [[PubMed](#)]
9. Huo, J.; Zhao, Z.; Han, G.; Xu, B.; Nan, Y.; Zhang, H.; Zhang, Z. Quantitative Study on Whole Canopy Leaf Area and Daily Transpiration and Photosynthetic Carbon Assimilation of *Caragana korshinskii*. *Physiol. Plant.* **2025**, *177*, e70618. [[CrossRef](#)] [[PubMed](#)]
10. Wu, X.; Fan, W.; Du, H.; Ge, H.; Huang, F.; Xu, X. Estimating Crown Structure Parameters of Moso Bamboo: Leaf Area and Leaf Angle Distribution. *Forests* **2019**, *10*, 686. [[CrossRef](#)]
11. Huang, F.; Fan, W.; Du, H.; Xu, X.; Wu, J.; Zheng, M.; Du, Y. Estimation of Leaf Area Index of Moso Bamboo Canopies. *J. Sustain. For.* **2021**, *42*, 189–204. [[CrossRef](#)]
12. Wu, Y.Y.; Dong, W.Y.; Pu, C.; Xie, Z.X.; Zhong, H.; Li, J.; Zhang, W. Biomass of accumulation and allocation characteristics of *Qiongzhueta tumidinoda* components and its relationship with soil physical properties. *Acta Ecol. Sin.* **2022**, *42*, 3516–3524. [[CrossRef](#)]

13. Huang, A.M.; Fang, Y.; Sun, J.; Li, J.L.; Hu, D.D.; Zhong, Q.L.; Cheng, D.L. Fine root traits of *Phyllostachys edulis* at different altitudes in Wuyi Mountain. *Acta Ecol. Sin.* **2023**, *43*, 398–407. [\[CrossRef\]](#)
14. Rožman, M.; Kišić, A.; Oreški, D. Comparative Analysis of Nonlinear Models Developed using Machine Learning Algorithms. *WSEAS Trans. Inf. Sci. Appl.* **2024**, *21*, 303–307. [\[CrossRef\]](#)
15. Antúnez, P.; Wehenkel, C.; Basave-Villalobos, E.; Calixto-Valencia, C.; Valenzuela-Encinas, C.; Ruiz-Aquino, F.; Sarmiento-Bustos, D. Predictive Modeling of Volume and Biomass in *Pinus pseudostrobus* Using Machine Learning and Allometric Approaches. *For. Sci. Technol.* **2025**, *21*, 110–122. [\[CrossRef\]](#)
16. Ramampandra, E.; Scheidegger, A.; Wydler, J.; Schuwirth, N. A comparison of machine learning and statistical species distribution models: Quantifying overfitting supports model interpretation. *Ecol. Model.* **2023**, *481*, 110353. [\[CrossRef\]](#)
17. Kupidura, P.; Kępa, A.; Krawczyk, P. Comparative analysis of the performance of selected machine learning algorithms depending on the size of the training sample. *Rep. Geod. Geoinform.* **2024**, *118*, 53–69. [\[CrossRef\]](#)
18. Manasa, P.A.; Salimath, S.K.; Dechamma, D.N.; Hegde, R.; Gooli, M. *Dendrocalamus brandisii* (Munro) Kurz: Unveiling the Significance of an Essential Bamboo Species. *Int. J. Plant Soil Sci.* **2023**, *35*, 124–131. [\[CrossRef\]](#)
19. Li, Z.; Guan, F.; Zhou, X.; Liu, L.; Fu, D.; Zhang, X.; Li, M. Effect of fertilization on soil fertility and individual stand biomass in strip cut Moso bamboo (*Phyllostachys edulis*) forests. *Forests* **2024**, *15*, 252. [\[CrossRef\]](#)
20. Xiang, Y.; Utsumi, Y.; Koga, S.; Kume, T.; Nagai, S.; Yang, M. Age-Dependent Plasticity in Hydraulics and Allocation of K, Si, and Starch in Moso Bamboo (*Phyllostachys pubescens*). *Physiol. Plant.* **2026**, *178*, e70745. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Singnar, P.; Nath, A.; Das, A. Culm characteristics and volume-weight relationship of a forest bamboo (*Melocanna baccifera* (Roxb.) Kurz) from northeast India. *J. For. Res.* **2015**, *26*, 841–849. [\[CrossRef\]](#)
22. Breda, N. Ground-based measurements of leaf area index: A review of methods, instruments and current controversies. *J. Exp. Bot.* **2003**, *54*, 2403–2417. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Parker, G. Tamm review: Leaf Area Index (LAI) is both a determinant and a consequence of important processes in vegetation canopies. *For. Ecol. Manag.* **2020**, *477*, 118496. [\[CrossRef\]](#)
24. Haghshenas, A.; Emam, Y. Accelerating leaf area measurement using a volumetric approach. *Plant Methods* **2021**, *18*, 61. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Kaushal, R.; Islam, S.; Tewari, S.; Tomar, J.M.S.; Thapliyal, S.; Madhu, M.; Trinh, T.L.; Singh, T.; Singh, A.; Durai, J. An allometric model-based approach for estimating biomass in seven Indian bamboo species in western Himalayan foothills, India. *Sci. Rep.* **2022**, *12*, 7527. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Li, L.; Yen, T.; Lin, Y. A generalized allometric model for predicting aboveground biomass across various bamboo species. *Biomass Bioenergy* **2024**, *184*, 107215. [\[CrossRef\]](#)
27. Baskerville, G.L. Use of Logarithmic Regression in the Estimation of Plant Biomass. *Can. J. For. Res.* **1972**, *2*, 49–53. [\[CrossRef\]](#)
28. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
29. Fife, D.; D’Onofrio, J. Common, uncommon, and novel applications of random forest in psychological research. *Behav. Res. Methods* **2021**, *55*, 2447–2466. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Smola, A.; Scholkopf, B. A tutorial on support vector regression. *Stat. Comput.* **2004**, *14*, 199–222. [\[CrossRef\]](#)
31. Zhang, F.; O’Donnell, L.J. Support vector regression. In *Machine Learning*; Mechelli, A., Vieira, S., Eds.; Academic Press: Cambridge, MA, USA, 2020; pp. 123–140. [\[CrossRef\]](#)
32. Arlot, S.; Celisse, A. A survey of cross-validation procedures for model selection. *Stat. Surv.* **2009**, *4*, 40–79. [\[CrossRef\]](#)
33. Qiu, J. An Analysis of Model Evaluation with Cross-Validation: Techniques, Applications, and Recent Advances. *Adv. Econ. Manag. Political Sci.* **2024**, *99*, 69–72. [\[CrossRef\]](#)
34. Peper, P.J.; McPherson, E.G.; Mori, S.M. Equations for Predicting Diameter, Height, Crown Width, and Leaf Area of San Joaquin Valley Street Trees. *Arboric. Urban For.* **2001**, *27*, 306–317. [\[CrossRef\]](#)
35. Zhou, Z.; Tang, Y.; Xu, H.; Wang, J.; Hu, L.; Xu, X. Dynamic Changes in Leaf Biomass and the Modeling of Individual Moso Bamboo (*Phyllostachys edulis* (Carrière) J. Houz) under Intensive Management. *Forests* **2022**, *13*, 693. [\[CrossRef\]](#)
36. Waring, R.H.; Schroeder, P.E.; Oren, R. Application of the pipe model theory to predict canopy leaf area. *Can. J. For. Res.* **1982**, *12*, 556–560. [\[CrossRef\]](#)
37. West, G.; Brown, J.; Enquist, B. A general model for the structure and allometry of plant vascular systems. *Nature* **1999**, *400*, 664–667. [\[CrossRef\]](#)
38. Enquist, B.J.; Allen, A.P.; Brown, J.H. Biological scaling: Does the exception prove the rule? *Nature* **2007**, *445*, E9–E10. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Xing, Y.H.; Jin, Q.Q.; Jiu, L.X.; Jian, F.H.; Bai, D.Q.; Si, M.C. Variation in Anatomical Characteristics of Bamboo, *Bambusa rigida*. *Sains Malays.* **2015**, *44*, 17–23. [\[CrossRef\]](#)

40. Yang, D.; Wang, X.; Yin, M.; Zhang, Y.-J.; Peng, G.; Tyree, M.T. An analytical complete model of root pressure generation: Theoretical bases for studying hydraulics of bamboo. *Plant Cell Environ.* **2024**, *47*, 59–71. [[CrossRef](#)] [[PubMed](#)]
41. Yang, D.; Zhang, Y.; Zhou, D.; Zhang, Y.-J.; Peng, G.; Tyree, M.T. The hydraulic architecture of an arborescent monocot: Ontogeny-related adjustments in vessel size and leaf area compensate for increased resistance. *New Phytol.* **2021**, *231*, 273–284. [[CrossRef](#)] [[PubMed](#)]
42. Bahru, T.; Ding, Y. Effect of stand density, canopy leaf area index and growth variables on *Dendrocalamus brandisii* (Munro) Kurz litter production at Simao District of Yunnan Province, southwestern China. *Glob. Ecol. Conserv.* **2020**, *23*, e01051. [[CrossRef](#)]
43. Chantararat, P.; Poolsiri, R.; Wannalangka, I.; Kaitpraneet, S.; Puangchit, L.; Jenke, M. Aboveground Biomass Productivity and Nutrient Use Dynamics of Clumping Tropical Bamboos in Northern Thailand. *Forests* **2023**, *14*, 1450. [[CrossRef](#)]
44. Gu, H.; Zhang, C.; Wang, J.; Shi, X.; Xia, R.; Liu, B.; Chen, F.; Bu, W. Variation in basic morphological and functional traits of Chinese bamboo. *Biodivers. Sci.* **2019**, *27*, 585–594. [[CrossRef](#)]
45. Li, H.-T.; Han, X.G.; Wu, J.-G. Lack of Evidence for 3/4 Scaling of Metabolism in Terrestrial Plants. *J. Integr. Plant Biol.* **2005**, *47*, 1173–1183. [[CrossRef](#)]
46. Niklas, K.J.; Cobb, E. Evidence for “diminishing returns” from the scaling of stem diameter and specific leaf area. *Am. J. Bot.* **2008**, *95*, 549–557. [[CrossRef](#)] [[PubMed](#)]
47. Fu, Q.; Shi, P.; Gielis, J.; Niklas, K.J. Non-destructive prediction of shoot-level leaf area and biomass in *Indocalamus* bamboo via scaling laws. *Front. Plant Sci.* **2025**, *16*, 1650196. [[CrossRef](#)] [[PubMed](#)]
48. Niklas, K.J. The Scaling of Plant Height: A Comparison Among Major Plant Clades and Anatomical Grades. *Ann. Bot.* **1993**, *72*, 165–172. [[CrossRef](#)]
49. Liese, W.; Weiner, G. Ageing of bamboo culms. A review. *Wood Sci. Technol.* **1996**, *30*, 77–89. [[CrossRef](#)]
50. Li, X.; Ye, C.; Fang, D.; Zeng, Q.; Cai, Y.; Du, H.; Mei, T.; Zhou, G. Non-structural carbohydrate and water dynamics of Moso bamboo during its explosive growth period. *Front. For. Glob. Change* **2022**, *5*, 938941. [[CrossRef](#)]
51. Shi, P.J.; Li, Y.R.; Niinemets, Ü.; Olson, E.; Schrader, J. Influence of leaf shape on the scaling of leaf surface area and length in bamboo plants. *Trees* **2021**, *35*, 709–715. [[CrossRef](#)]
52. Yen, T.-M.; Sun, P.-K.; Li, L.-E. Predicting Aboveground Biomass and Carbon Storage for Ma Bamboo (*Dendrocalamus latiflorus* Munro) Plantations. *Forests* **2023**, *14*, 854. [[CrossRef](#)]
53. Fan, G.; Nan, L.; Chen, F.; Dong, Y.; Wang, Z.; Li, H.; Chen, D. A New Quantitative Approach to Tree Attributes Estimation Based on LiDAR Point Clouds. *Remote Sens.* **2020**, *12*, 1779. [[CrossRef](#)]
54. Evans, M.R.; Moustakas, A. A comparison between data requirements and availability for calibrating predictive ecological models for lowland UK woodlands: Learning new tricks from old trees. *Ecol. Evol.* **2016**, *6*, 4812–4822. [[CrossRef](#)] [[PubMed](#)]
55. Seymour, R.S. Leaf area prediction models for *Tsuga canadensis* in Maine. *Can. J. For. Res.* **1999**, *29*, 1574–1582. [[CrossRef](#)]
56. Zhang, Y.; Yue, X.H.; Qi, L.H.; Jiang, Z.H.; Shi, L. Estimation of *Phyllostachys edulis* forest biomass in southern Wuyishan Mountain using allometric equation and geostatistical technique. *Chin. J. Ecol.* **2016**, *35*, 1957–1962. [[CrossRef](#)]
57. Jiang, R.; Lin, J.; Li, T. Refined Aboveground Biomass Estimation of Moso Bamboo Forest Using Culm Lengths Extracted from TLS Point Cloud. *Remote Sens.* **2022**, *14*, 5537. [[CrossRef](#)]
58. Bernard, S.; Adam, S.; Heutte, L. Dynamic Random Forests. *Pattern Recognit. Lett.* **2012**, *33*, 1580–1586. [[CrossRef](#)]
59. Matsuki, K.; Kuperman, V.; Van Dyke, J. The Random Forests statistical technique: An examination of its value for the study of reading. *Sci. Stud. Read.* **2016**, *20*, 20–33. [[CrossRef](#)] [[PubMed](#)]
60. Shi, K.; Qiao, Y.; Zhao, W.; Wang, Q.; Liu, M.; Lu, Z. An improved random forest model of short-term wind-power forecasting to enhance accuracy, efficiency, and robustness. *Wind Energy* **2018**, *21*, 1383–1394. [[CrossRef](#)]
61. Vabalas, A.; Gowen, E.; Poliakov, E.; Casson, A.J. Machine learning algorithm validation with a limited sample size. *PLoS ONE* **2019**, *14*, e0224365. [[CrossRef](#)] [[PubMed](#)]
62. Huang, W.; Su, X.; Ratkowsky, D.A.; Niklas, K.J.; Gielis, J.; Shi, P. The scaling relationships of leaf biomass vs. leaf surface area of 12 bamboo species. *Glob. Ecol. Conserv.* **2019**, *20*, e00793. [[CrossRef](#)]
63. Shi, P.; Liu, M.; Ratkowsky, D.A.; Gielis, J.; Su, J.; Yu, X.; Wang, P.; Zhang, L.; Lin, Z.; Schrader, J. Leaf area–length allometry and its implications in leaf shape evolution. *Trees* **2019**, *33*, 1073–1085. [[CrossRef](#)]
64. West, G.B.; Brown, J.H.; Enquist, B.J. A general model for the origin of allometric scaling laws in biology. *Science* **1997**, *276*, 122–126. [[CrossRef](#)] [[PubMed](#)]
65. Duncanson, L.; Rourke, O.; Dubayah, R. Small Sample Sizes Yield Biased Allometric Equations in Temperate Forests. *Sci. Rep.* **2015**, *5*, 17153. [[CrossRef](#)] [[PubMed](#)]
66. Turner, M.G.; Tinker, D.B.; Romme, W.H.; Kashian, D.M.; Litton, C.M. Landscape patterns of sapling density, leaf area, and aboveground net primary production in postfire lodgepole pine forests, Yellowstone National Park (USA). *Ecosystems* **2004**, *7*, 751–775. [[CrossRef](#)]

67. Putney, J.D.; Maguire, D.A. Shifts in foliage biomass and its vertical distribution in response to operational nitrogen fertilization of Douglas-fir in western Oregon. *Forests* **2020**, *11*, 511. [[CrossRef](#)]
68. Li, L.; Wen, Y.; Xu, J.; Bai, T.; Yang, M.; Jiang, W. Different Parts of a *Dendrocalamus brandisii* (Munro) Kurz Shoot, Rather Than the Shoot's Height, Are More Indicative of Its Nutrient Properties. *Horticulturae* **2024**, *10*, 438. [[CrossRef](#)]

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