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Models for Predicting Tree Diameter at Breast Height from Over and Under Bark Diameter of Stump in *Eucalyptus camaldulensis* Plantations

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ABSTRACT

Allometric functions that predict tree diameter at breast height (D) from stump diameter (DS), referred to as DS-D models, are essential for estimating forest metrics like stand volume and belowground carbon (C), especially when D cannot be measured, such as after inadequately recorded clearcutting or illegal logging of threatened species. Many available DS-D models are generic for diverse species and ecological condition, and are largely based on DS measured over bark (DSoB). Studies show that bark thickness (BT), a factor of DSoB, varies intra-species and across ecosystems as a response to fire history and other ecological factors. This raises concerns about the reliance on generic, DSoB-based models for inventory on regenerating clearcut plantation sites.

We hypothesize that local DS-D models calibrated with DS under bark (DSuB) better account for *in-situ* ecological variability in BT. To test this, we gathered data through destructive and non-destructive sampling of clonally propagated (CP), post-fire recovery (FR), and coppice-regenerated (CR) stands of monoculture *Eucalyptus camaldulensis* plantations (ECPs) in East Africa. Using the data, we employed machine learning and traditional statistical methods to calibrate DS-D models, alternately based on DSoB and DSuB as predictor variables. Through error residuals and effect sizes analyses, we compared (1) the performance of previously published, *ex-situ* generic DS-D equations versus the study-derived local models, (2) the effectiveness DSoB versus DSuB for DSoB both as the predictor and the input variables for DS-D models, and (3) assessed the statistical variation of DS-D models between post-fire recovery and non-fire impacted ECP stands.

The results showed that (1) *in-situ* models outperformed *ex-situ* equations (2) substituting DSoB with DSuB as regressors improved model accuracy, (3) DSoB substitution with DSuB as input variable did not reduce the performance of DSoB-based models. and (4) modeling of DS-D allometry post-fire recovery stand was complicated by high heterogeneity in tree diameter classes.

These findings show that recalibrating DSoB-based models with DSuB can better capture DS-D allometry due to the circumvention of local environmental effects on BT. The findings further confirm the utility of DS-D models even when the stump's bark layer is missing.

Keywords: Stump diameter, bark thickness, post-fire recovery, stump diameter over bark, stump diameter under bark, *Eucalyptus camaldulensis* plantations, relative root mean squared error (RRMSE).

Introduction

The analysis of remnant stumps offers a practical approach to reconstructing pre-harvest biomass characteristics of logged forests, such as extracted timber volume and carbon (C) composition of the belowground structural components. Diameter at breast height (D) is the typical standard measure used to estimate C and other weight-related variables in forest inventories (Ercanli e(Ercanli *et al.*, 2015; Vanclay, 1994; Westfall & Mcroberts, 2017; Zanvoet *et al.*, 2023). However, obtaining D data is often unfeasible in inventory situations involving

undocumented logging, illegal harvests, or poaching of rare species (Antal, 1992.; Bylin, 1982; Ercanli *et al.*, 2015b; Pires & Marteache, 2023). In such cases, stump diameter (DS) serves as the most practical biometric parameter for estimating D, trunk height, tree volume, or biomass, provided the allometric relationship between DS and D has been defined and validated for the prevailing species or forest type (Ercanli *et al.*, 2015b).

Allometric modeling is a feasible and environmentally sound method relying on the axiomatic relationships between growth components to build mathematical models (functions) for predicting target dendrometric parameters of trees from a more easily measured weight variable. Allometric models are essential for sustainable forest management as they provide insight into the C storage of woodlots and convenience in estimating the bioenergy output of plantation projects (Mulatu *et al.*, 2024). Models based on allometric relationships between DS and D (i.e., DS-D models) have been validated and deployed in forest inventories globally to reconstruct stand conditions, develop localized volume equations, and estimate C stocks where direct D measurements are impractical (Bylin, 1982; Demaerschalk & Omule, 1982; Kozak & Omule, 1992; Özçelík *et al.*, 2010). They are vital for evaluating how well ECP-based afforestation projects have done regarding C sequestration belowground or the losses incurred aboveground in tree plantations recovering from inadequately documented clearcut harvests.

Some currently used allometric models are generic, while others are site- or species-specific (Mulatu *et al.*, 2024). Generic DS-D models have been derived globally for key species and

broad forest types (Di Cosmo & Gasparini, 2020; Gonzalez-Benecke *et al.*, 2021; Horvath A & Popa A, 2021). In short-rotation plantations, including ECPs, a lack of validated, locally derived DS-D models results in the reliance on externally derived generic functions. There is a research concern that such broad category models do not account for intra-species variation in growth allometry resulting from the history of fire and other local disturbances. Although some recent studies favor the continuing local use of generic models for their simplicity and broader applicability (Alvarez *et al.*, 2012; Schafer *et al.* (2015); Lau *et al.*, 2019; Vieilledent, 2012).

However, other recent studies highlight that the accuracy of broad-category models often varies when applied to new ecosystems or regions lacking localized equations, such as tropical tree plantations. Instead, these studies demonstrate that site- and species-specific models can improve inventory accuracy by accounting for local ecological factors. Such factors may include variances caused by cultivar differences, silvicultural spacing practices, and other site-specific conditions (Chukwu *et al.*, 2020; Dey *et al.*, 2021; Kuyah & Rosenstock, 2015; Mugasha *et al.*, 2021; Mulatu *et al.*, 2024).

A key but underexplored aspect of DS-D modeling is the choice between DS measured over bark (DSoB) and DS measured under bark (DSuB). Although DSoB is more commonly used, Bylin (1982) partially explored DSuB, and Kozak & Omule (1992) recalibrated a DSoB-based model by Demaerschalk and Omule (1982) using DSuB. Corral-Rivas *et al.* (2007) later developed a DSuB-based equation for pine species in Mexico. These studies offered valuable insights and practical

biomass and C accounting models. However, there is a growing research need to build on the existing models and further explore DS-D modeling by comparative assessment of DSoB and DSuB as predictor variables. Current knowledge that bark thickness (BT), the main difference between DSoB and DSuB, varies by species, and intra-species due to tree response to fire history (Schafer *et al.* (2015) and other ecological conditions (Konôpka *et al.*, 2022). Other studies further show that smaller trees ($D \leq 10$ cm) have higher bark volume proportions (42%) compared to larger trees ($D \geq 50$ cm) at 3% (Neumann & Lawes, 2021a; Wilms *et al.*, 2021).

On one level, recent studies highlight the need to evaluate empirical models especially to better account growth allocation in post-fire recovery plantations (Hoods *et al.* 2018), where trees are hypothesized to select for higher investment in BT (Schafer *et al.* 2015). On another level, DSoB-based models tend to inherently assume that DS measurements are taken over bark, which is incidentally the tree component often missing or intensively damaged tree parts (Konôpka *et al.*, 2022). The DSuB could, thus, be a more reliable parameter and input variable for DS-D models.

This study addresses the following questions: (1) How accurate are *ex-situ* generic equations compared to site- and species-specific DS-D models? (2) How does the choice between DSoB and DSuB affect model accuracy in ECPs, considering potential intraspecies bark thickness variation? (3) Do species-specific DS-D models for ECPs based on DSoB adequately account for tree investment in bark in stands with fire history. Additionally, we asked whether DSuB can effectively substitute DSoB as an input variable in DS-D models calibrated with DSoB as predictor variables? These questions remain unaddressed in the literature, particularly for ECPs, which are driving

afforestation expansion and emerging as functional alternatives and buffersto natural forests in Sub-Saharan Africa.

To address these research questions, we collected D, DSoB, and DSuB data through destructive and non-destructive sampling of three distinct classes of ECP, namely (i) first rotation clonally-propagated (CP) stands, (ii) a post-fire recovery (FR) stand, and (iii) coppice-regenerated (CR) second rotation plots. Using subsets of the data, we calibrated and validated models for estimating D from DS in monocultural ECPs in East Africa, alternatively using DSoB and DSuB as predictors. With holdout (subsets) of the datasets, we evaluated and compared the predictive accuracies of three reference models versus the study-derived functions. We calibrated a specific function for the FR stand and compared its prediction with those of models optimized for the general class of ECPs. Wethen compared DSoB versus DSuBas model regressor andinput variables in DS-D model estimation.

Previous studies found that allometric model selection is often the largest source of error, contributing up to 76% of inaccuracies in forest biomass and C estimations(Picard et al.,2016). This error is more pronounced in post-fire recovery forest plantation where mechanisms governing stem growth and relative BT accumulation are remain largely underexplained (Hoods et al., 2018). Our study-derived model aimed tohelp bridge these knowledge gap by calibrating and validating DS-D models three classes of ECP, including post-fire recovery stands (FR).The foundational model presented in the study has management implication, given that wildfire has

been identified as a major deterrent to investment in tree plantations, particularly in developing tropical countries (Andrew, 2022).

Under the current dearth of validated DS-D models, even minor prediction errors of unvalidated ex-situ functions magnify over large areas, leading to significant resource overestimation or undervaluation (Aneseyee *et al.*, 2016). The optimized species-specific models presented by the study can be extrapolated and evaluated for resource estimation in logged monocultural plantations of *Eucalyptus* and other tropical species with growth allometry similar to that of ECPs. In addition to the optimized models, the study presents early-stage functions that can be refined with additional data and deployed to estimate C composition, merchantable timber volumes, and overall vegetation recovery in post-fire plantations.

Method

Research Design

We began by selecting three ex-situ broad category DS-D functions to serve as reference models for our analysis. These functions were as follows: (1) the DS-D equation developed by Özçelîket *al.* (2010) for short-rotation tree species, specifically Brutian pine; (2) the DS-D function formulated by Mugasha *et al.* (2021) for cultivated forests and woodlots in East Africa; and (3) the Horvath and Popa (2021) model for monocultural plantations under silvicultural practice of logging at the stump height of 30 cm, corresponding to the cutting height in our study region (Table 1).

Table 1. The reference models selected for evaluation

Author	Species/forest type	Coefficient	
		β_0	β_1
Horvath & Popa (2021)	Broad class if DS height = 30cm	3.252	0.753
Özçelíket <i>al.</i> (2009)	Brutian pine	- 0.2682	0.9036
Mugashaet <i>al.</i> (2021)	Plantation & cultivated forests	0.5514	0.7578

Next, we carried out field sampling to obtain in-situ datasets of DSoB, DSuB, and D from each of the three classes of ECPs (i.e., CP, FR, and CR). We then used the field-derived data to train initial candidate DS-D models. The predictive performances of the candidate models were then compared with those of the selected reference equation through a series of validation tests. Based on the primary candidate models' performance, two high-performance models were calibrated by data optimization. Figure 1 depicts this research framework.

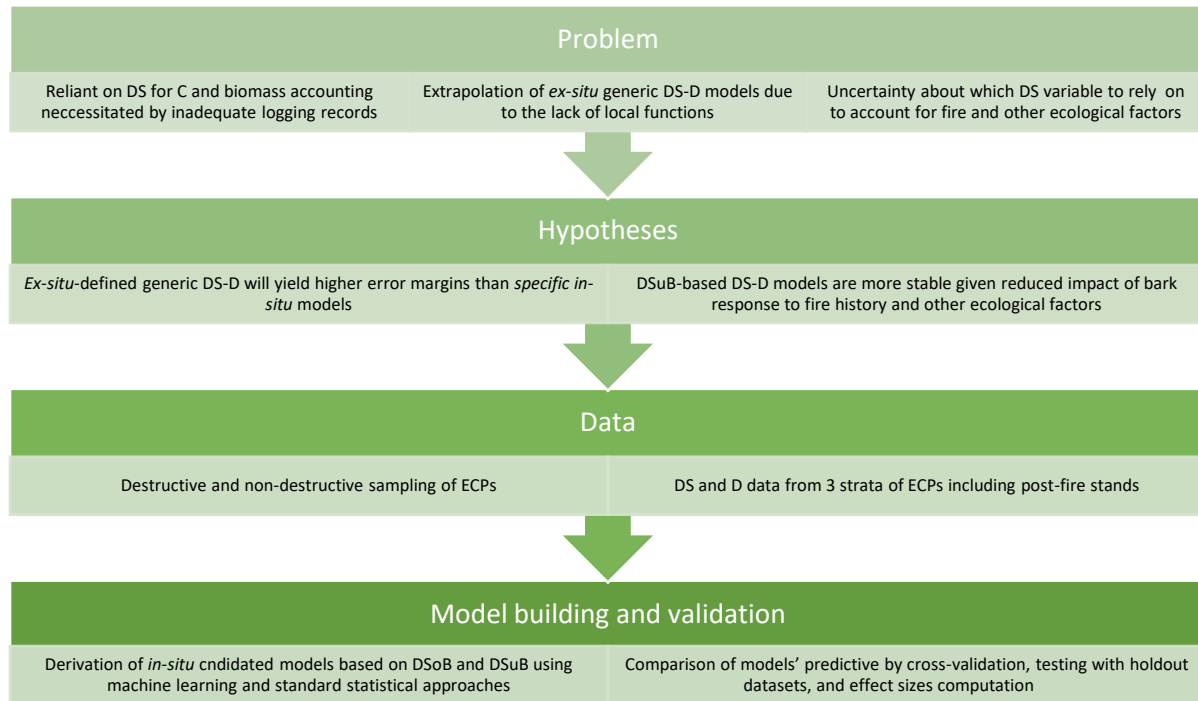


Figure 1. Schematic diagram of the study methodology showing the research progression through the problem identification, hypotheses formulation, observation, and modeling stages.

Study Area

The study was conducted in Msambweni District, Kwale County, in southern Kenya (4°10'17"S, 39°13'3"E; altitude 30–160 m). The region falls under the tropical dry savanna climate (Köppen classification), with an average annual rainfall of 1,100 mm. Land use is dominated by agriculture, forest conservation, hospitality, and mining. Lafarge Ecosystems—the sustainability arm of one of the several multinational mining companies operating in the area—has a long history of land reclamation and ecological restoration of mining-degraded surfaces through large-scale establishment of ECPs and other types of short-rotation tree plantations. Overall, fast-growth tree plantations, dominated by ECPs, represent an expanding landscape feature and forest growth spots in Msambweni District and Kwale County. While Shimba Hills Forest Reserve is the most notable forest in Kwale, Msambweni hosts three other important forests in the county:

Mrima, Nzombo, and Marenje. The first of the two sampling sites for this study was located at the edge of Marenje Forest, and the other was situated about 3 kilometers north of the forest. Figure 2 shows a map of the study area in Kwale County, Kenya. The map was produced using version 3.40.0 of the QGIS software and its in-built library.

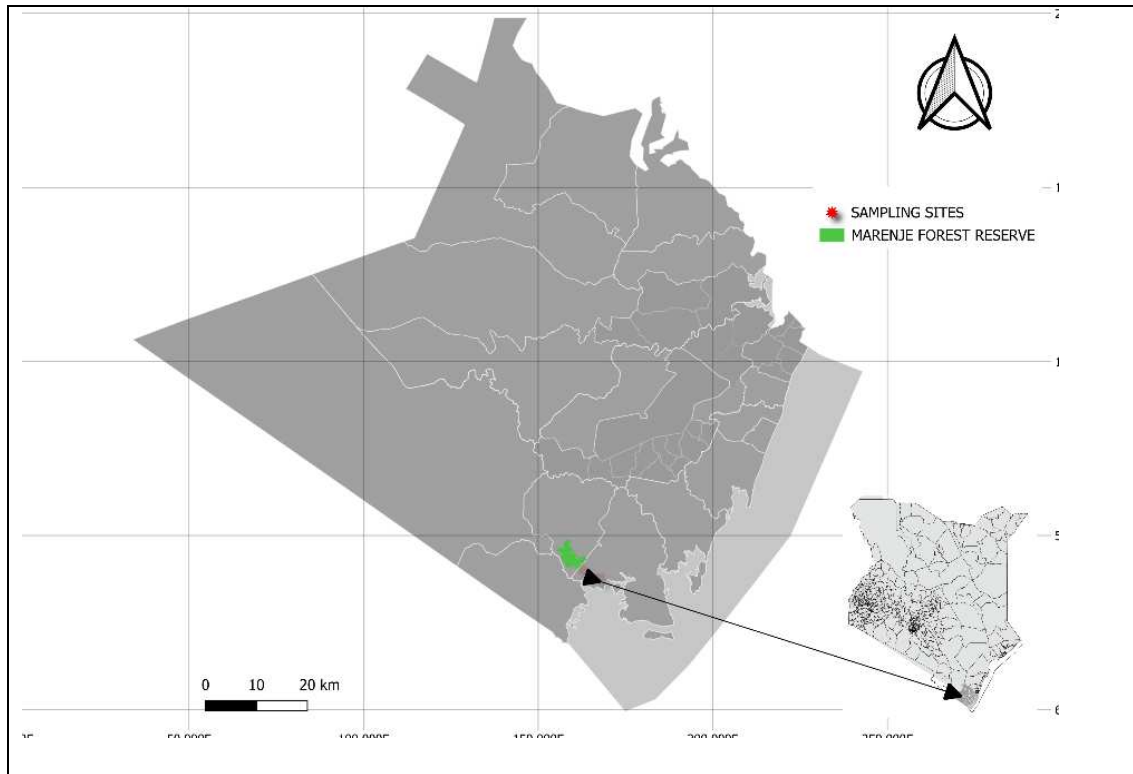


Figure 2. Map of the study area in southern Kenya showing the sampling sites and the neighboring Marenje Forest Reserve

Study plantation contexts

Each sampling site comprised monocultural ECP stands and was situated within the Marenje-Majoreni axis of the Msambweni District. The first sampling site was a 115-hectare contiguous plantation adjacent to Marenje Forest. Sampling at this site could be easily divided into three distinct classes reflecting the plantation's establishment and management history. As such, the

study delimited three study strata: a 14-year-old CP stand, a 9-year-old FR segment, and a CR stand at the 9th year of reestablishment following the first rotation harvest.

In the CP stratum, the contiguous spacing of trees was noticeably broken by gaps taken up by cohort assemblages of non-planted native vegetation. In the FR section of the plantation, this cohort vegetation assemblage was not observed, possibly because the severe fire incident at the initial establishment stage disrupted such successional association, for example, through seed bank destruction. The cohort assemblage was also missing in the CR plots, probably mitigated by the gap planting after the initial clearcut harvesting.

The smaller sampling site was a first rotation woodlot on a 27-acre area closer to the Majoreni Village, about 3 kilometers north of Marenje Forest. The stand comprised 9-10-year-old uniformly spaced (2.5 x 5 m) clonally-propagated trees. The stand establishment followed similar pre-planting and planting methods but differed by management intensity from the first study site. The cohort assemblage of unplanted species did not occur in this stand, as was observed at the bigger sampling site.

Field sampling

Destructive sampling was conducted during a planned clearcut harvest at the first sampling site in October 2022. The non-destructive sampling occurred between September 2023 and January 2024, focusing only on D and DSoB, measured approximately 30 cm above ground following the standard local silvicultural practices. The destructive sampling allowed for a direct

measurement of DSoB and DSuB over the cross-sectional surface of stumps of the felled trees without reliance on bark thickness gauge. Measurements at the second site were non-destructive, focusing on D and DSoB only.

Sample selection and data collection

Trees were selected using a systematic line transect method. The transects were set at 20 m intervals. The location of the first transect line followed a random process. The outer two rows of each plot were excluded in the randomization process to minimize edge effects. The D for each sampled stem was measured over bark at 1.3 m height. For stems with multiple trunks, each stem measuring over 10 cm was individually measured and aggregated into a composite stem measurement. A total of 117 trees were sampled in all (64 destructively, 53 non-destructively).

The range of sample size was similar to that used by Koreň *et al.* (2024) in evaluating methods of predicting D from stumps in European Beech forests and the 59 tree samples used by Mulatu *et al.* (2024) for allometric modeling of Moist Afromontane of Ethiopia. This range of sampling size does not depart from recent allometric modeling study designs. In the extensive review of biomass equations in Europe by Zianis *et al.* (2005), up to 75% of allometric models examined were based on destructive or non-destructive sampling of 50 trees or less. Given the robustness of our model calibration approach, we assume the sample size used in this study is adequate for the research purpose with a focus on a single species under a standardized uniform planting. Nonetheless, datasets in this study were subjected to rigorous tests to satisfy the ordinary least squares (OLS) modeling assumptions.

In each destructively sampled tree, all structural weight variables above the stump were measured for this study and other research projects. Only the DSoB, DSuB, and D measurements were recorded for this study. Among the destructively sampled trees, the DSoB was measured using a metric tape and recorded as the total cross-sectional diameter of the cut stump surface. The DSuB measurements were recorded as the total cross-sectional diameter of the wood segment of the cut stump surface. Only D and DSoB measurements were taken from the non-destructively sampled trees, with stump height following the region silvicultural practice of tree cutting at approximately 30 cm from the tree base.

Statistical analysis method

All statistical analyses, including descriptive, predictive, and inferential statistics, were performed using IBM SPSS Statistics, Version 28.0.0 (2024), and MATLAB (The MathWorks, 2024). The D and DSoB measurements were recorded for all 117 trees in the study, while DSuB were recorded for a subset of 64 (destructively sampled) individual stems. The DSoB samples ranged from 4–8 cm, while DSuB ranged from 3–6 cm, as shown in the summary statistics in Table 2.

Table 2. Summary statistics of all the test variables

DATA	RANGE	MINIMUM	MAXIMUM	MEAN	SKEWNESS
DSOB	28.00	4.00	32.00	14.85	0.43
DSUB	26.0	3.0	29.0	12.73	0.45
D	26.00	2.00	28.00	11.67	0.40

Note: N = sample size. DSoB, DSuB, D in centimeter measurements

After organizing the data into matrices of DSoB, DSuB, and D for each of the three strata of the experimental ECPs (i.e., CP, FR, and CR stands), the datasets were evaluated for compliance with Ordinary Least Squares (OLS) regression assumptions. Possible outlier presence was assessed visually by boxplot inspection and statistically by Z-score analysis. Linearity between dependent and independent variables was evaluated by visual inspection of scatterplots and ANOVA tables generated in univariate general linear model (GLM) analyses. Normality assessment was done using both the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests to account for the variation in sample sizes between the CP, FR, and CR stands. Whereas S-W test has a higher power than other tests (Saculinggan&Balase,2013), the K-S test is more powerful with a larger sample size at a 5% significance level(Emmanuel *et al.*,2020).

For the homoscedasticity tests, first-run regression analyses were carried out to generate standardized predicted D variables and their corresponding standardized residual values. The residuals were converted to standardized residuals of their respective absolute values. The standardized residuals were then plotted against the standardized predicted variables to generate scatterplots for virtual inspection for heteroscedasticity likelihoods. Statistical tests of the heteroscedasticity hypothesis were done using Pearson's and Spearman's Correlations for each dataset, correlating the standardized predicted variables and the absolute values.

Modeling and model validations

As part of the OLS assumption tests, a machine learning iteration was employed to train seven (primary) candidate models alternately regressing DSoB and DSuB variables against their corresponding D variables. The primary models were based on segregated datasets of samples from the CP, FR, and CR stands. Models 1, 2, and 7 came from the CP sample dataset, models 3 and 4 were based on samples from the FR stand, while data for 5 and 6 were built using data from the CR stand. Models 1 to 6 were trained using data from destructively sampled plots. The holdout datasets were derived by both destructive and non-destructive sampling. Whereas models 1, 3, 5, and 7 used DSoB as predictor variables, models 4 and 6 were based on DSuB.

Each candidate model was evaluated based on statistical significance (p-value), explanatory power (R^2), and sums of squared errors (SSE) of the coefficients. Models with R^2 values below 0.500 were excluded from further analysis, and datasets for their parametrization were set aside as additional holdout data for model testing, especially pertaining to the comparative assessment of DSoB and DSuB as input variables. Data for the retained models were retrained and subjected to 5-fold cross-validation tests at a split ratio of 80:20 (training: testing) using the Regression Learner App in MATLAB (The MathWorks, 2024). Insights from the cross-validation results and initial OLS variance homogeneity tests informed the development of two additional functions, models 8a and 8b. While model 8a was based on the recalibration of model 7 by DSoB data optimization, model 8b was optimized by aggregation of DSoB and DSuB variables.

Models 5, 6, 8a, 8b, and the three reference allometric equations were subjected to comparative predictive accuracy tests using holdout datasets. Two holdout datasets were merged into a larger dataset, randomized using Excel's RAND function, and split into portions to facilitate multi-level testing. To complement these assessments, the optimized models' consistency (predictive repeatability) was further evaluated using the dataset for the primary candidate models that had not advanced further in the study. The predictive accuracy of the models was evaluated by computing the root mean squared error (RMSE) between each model's estimates and corresponding observed D values (Alvarez *et al.*, 2012). To estimate the effect size of the models, we computed each model's relative RMSE (RRMSE), normalized separately by the range and mean of the prediction-targeted value (i.e., the observed D value). The RRMSE computation was performed manually in Excel following the error weighing approach outlined by (Chen & Luc, 2022) as follows:

$$RRMSE = \frac{RMSE}{Range} \times 100;$$

and

$$RRMSE = \frac{RMSE}{Mean} \times 100$$

where the respective denominators are the range and mean values of the measured D variables.

Finally, we assessed the applicability of DSuB as the input variable in DS-D models built using DSoB as the predictor. The reference equations and the successful candidate models (those with predictive power exceeding 90%, i.e., $R^2 > 0.900$) were iteratively tested, alternately using DSoB and DSuB as inputs. Residuals from each test were recorded as separate variables and analyzed

using an F-test for means comparison and paired-samples t-test (at a 0.05 significance level) to determine the statistical significance of the error differences.

Ethical considerations

The authors conducted the study with proper consideration of the Finnish Guideline on Research Integrity, and the handling of the related datasets followed the data management guidelines of the University of Helsinki. The destructive sampling of trees carried out in the study coincided with management-planned rotational harvest, and therefore, did not result in additional environmental or ecological harm to the production ecosystem.

Availability of data and material

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Funding statement:

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Results

Assumption testing and model validation

As described in the methodology section, the study datasets were evaluated for the assumptions of OLS regression. Outliers were assessed using boxplots and Z-score analysis. Linearity was evaluated by scatterplots and the ANOVA table of the GLM analysis. Normality was statistically tested using the Kolmogorov-Smirnov and Shapiro-Wilk tests. Homoscedasticity was assessed by plotting absolute values of standardized residuals against standardized predicted variables and performing Pearson's and Spearman's correlations for heteroscedasticity. The findings from these statistical tests are summarized in this subsection.

Visual inspection of the boxplots suggested the presence of outliers in the destructively sampled portions of the DSoB and DSuB variables from the CP and FR stands. Statistical analysis confirmed this, with z-scores of 4.146 for a single datapoint each in the DSoB and DSuB variables of the FR sampling stratum. Since these values fell outside the Z-score's -3 to 3 acceptance range, we rejected the hypothesis of no outliers in the two datasets from the FR stand. A Z-score of 3.455 was recorded for one datapoint in datasets of the CP stand, which marginally fell outside the no outlier acceptance zone. However, because this Z-score was recorded in the dependent variables data, we proceeded with the assumption that there were no statistical outliers in the CP datasets. Scatter plots of the Z-score for all the test datasets are displayed in Figures 3a and 3b.

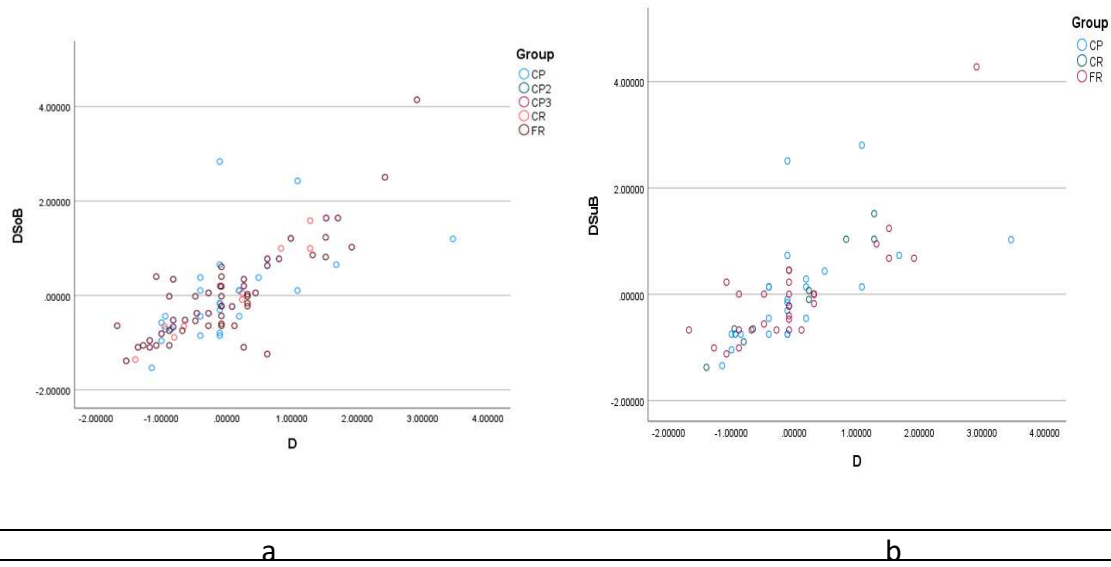


Figure 3. Scatter plots of Z-scores of outlier test of predictor and response variables. Figurea shows the Z-scores ofDSoB on the Y-axis. Figureb shows DSuB on the Y-axis. The D variable is plotted on the X-axis to highlight the outlier datapoint. CP2 and CP3 are non-destructively sampled CP datasets.

As shown in Table 3, the ANOVA table of GLM analysis F-values of statistical test for linearity of the sample datasets, deviation from linearity was not statistically significant for any of the datasets. The test results, therefore, reveal strong linear relationships between the different sets DS and D variables across all the three strata of sampled ECP stands.

Table 3. ANOVA Table of linearity test displaying linear relationships between the D and DS variables in all the experimental ECP classes.

Dataset	Model	Test	F	Sig.
DSoB - D	1	Linearity	19.40	.001
		Deviation	2.60	.069
DSuB - D	2	Linearity	20.68	<.001
		Deviation	2.57	.064
DSoB - D	3	Linearity	.100	>.001
		Deviation	1.24	.363
DSuB - D	4	Linearity	71.02	<.001
		Deviation	1.634	.181
DSoB - D	5	Linearity	105.44	.009
		Deviation	.802	.636
DSuB - D	6	Linearity	104.01	.009
		Deviation	.688	.682
DSoB - D (II)	7	Linearity	735.20	<.001

DSoB - D (I)	Test	Deviation	2.04	.116
		Linearity	129.98	<.001
		Deviation	2.54	.107

The matrix scatterplots in Figure 4a display a clear positive linear regression between the DS and D variables used to calibrate model 8b. Figure 4b shows the matrix of linearity between the DSoB, DSuB, and D variables along a theoretical model, while 3c shows the same relationship along the actual trend line. Both matrix cases show a tight linearity between DSoB, DSuB, and D, albeit with a slightly wider dispersion among a few large trees.

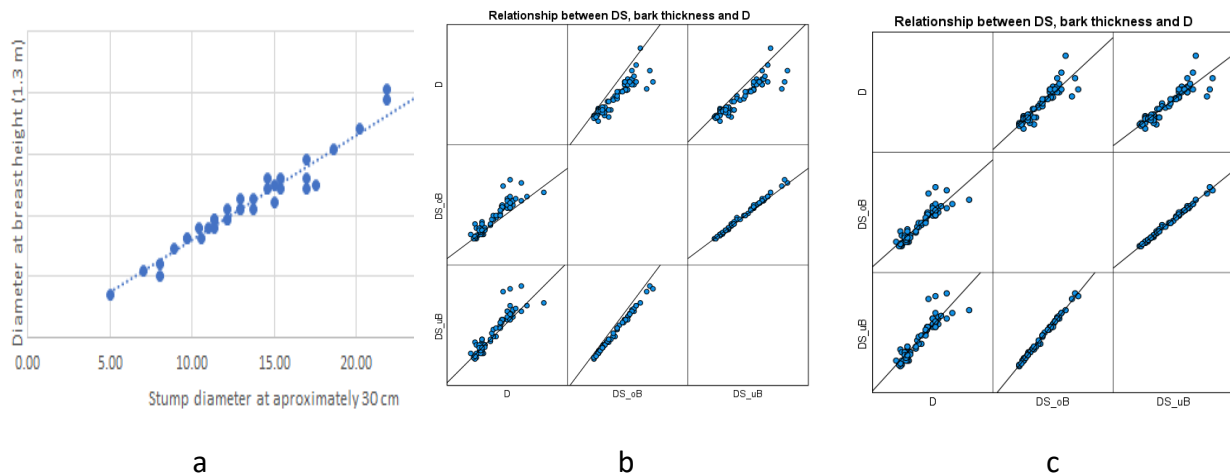


Figure 4. Linearity trends of the D and DS datasets. Figure 4a shows the linearity of the variables of the optimized DS-D dataset. Figure 4b shows a matrix of the DSoB, DSuB and the D along a theoretical model. Figure 4c shows the linearity of the variables along the actual trend line.

The Kolmogorov-Smirnov test results suggested a borderline case ($P = 0.094$), while the

Shapiro-Wilk indicated a clear departure from the normal distribution ($p = 0.005$) for the FRoB dataset. Both tests revealed a non-normal distribution ($p = 0.004$ and $p < 0.001$, respectively) for the FRuB).

Pearson's and Spearman's Correlations were not significant for any of the datasets. As such, we rejected the hypotheses of heteroscedasticity for each of the test datasets.

Findings

The preceding subsection highlighted the results of the statistical analyses to assess the test variables' compliance with OLS assumptions. This subsection of the results section presents the findings of this modeling and model validation procedures.

Upon the initial iteration of the different datasets in OLS regressions, all the resulting candidate models produced statistically significant p-values. The maximum p-values ($p = .004$ and $p = .003$) were recorded in generating models 1 and, respectively. The two models were built exclusively with the dataset from the CP stand. Whereas model 1 could explain 31% variation in D based on changes in DSoB, model had only a marginally bigger explanatory power, explaining up to 33% of the variance based on changes in DSuB. Compared to the other candidate models, the two functions produced the lowest t-statistics values (3.194 and 3.370, respectively). The coefficients of their respective slopes had higher standard errors (0.159 and 0.170, respectively) compared to 0.070 or less for each of the other models.

Models 3 and 4 showed a moderate-to-strong statistical significance ($p < .000$) with 67% and 66% predictive powers, respectively. Given the unique characteristics of the FR stand—the source of their datasets—both models were analyzed further in the study despite their average power of prediction and the presence of an outlier in their predictor variables. This approach was aimed to provide statistical insights and establish foundational functions in the literature for potential

refinement and deployment in post-fire recovery ECPs. Models 5, 6, and 7 all had a strong statistical significance ($p < .000$), predictive powers range of 72 – 95%, with comparatively higher t-statistics (t-value 7.8 to t-value 11.6). The descriptive metrics and coefficients of candidate models 1 – 7 are shown in Table 4.

Table 4. Coefficients, error estimates, and significance values of all the initial candidate (DS-D) models for predicting tree diameter at breast height (D) from stump diameter (DS). Functions 1-6 were alternately based on either DS over bark (DSoB) or DS under bark (DSuB) from the experimental *Eucalyptus camaldulensis* plantations (ECPs).

Model	Variable	Data source	a	b (slope)	R ²	SE	t	Sig.
1	DSoB	CP	5.365	0.509	0.307	0.159	3.194	< 0.004
2	DSuB	CP	5.188	0.573	0.331	0.170	3.370	< 0.003
3	DSoB	FR	2.326	0.429	0.674	1.456	7.614	< 0.000
4	DSuB	FR	2.552	0.459	0.662	0.662	7.408	< 0.000
5	DSoB	CR	-0.079	0.771	0.946	0.835	11.080	< 0.000
6	DSuB	CR	0.550	0.791	0.951	0.796	11.680	< 0.000
7	DSoB	CP	2.875	0.680	0.721	2.422	7.882	< 0.000

Note: a = intercept, b, R² = R-squared, SE = standard error of the coefficient (b), t = t-value, sig. = P-value

Figure 5 illustrates the initial predictive performance of reference DS-D models compared to the primary *in-situ* derived species-specific models within the experimental ECP stands. Among the reference models, the Mugashaet *al.* (2021) prediction was the most accurate, with a lower residual error (RMSE = 2.58 cm) compared to the Özceliket *al.* (2009) and Horvath and Popa (2021) models, which had RMSE values of 2.70 cm and 2.85 cm, respectively. As shown in the Figure 5 grid layout, the predictions from Mugashaet *al.* aligned more closely with observed D values than the other reference models, as evidenced by shorter lines joining predicted and actual data points. The Mugashaet *al.* model also performed better than most primary candidate models, except model 6 (RMSE = 2.45 cm).

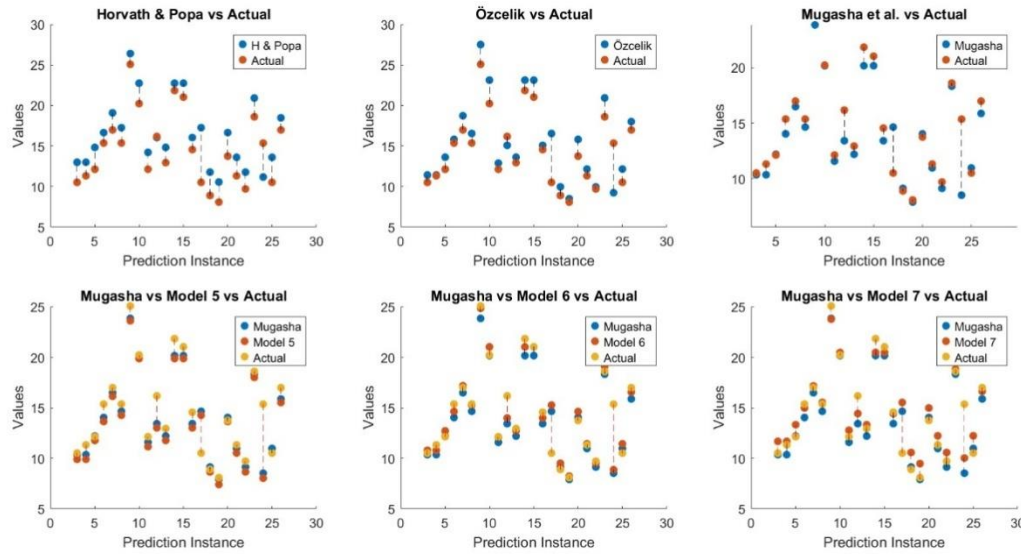


Figure 5. Results of the initial validation test to compare the predictive performance of reference ex situ DS-D models to local specific models using the second set of holdout dataset from sampled stands

The training and optimization response and the predicted versus actual plots of models 7, 8a, and 8b are shown in Figure 6. Upon the optimization of model 7 by aggregation of DSoB and D datasets, the recalibrated function (model 8a) achieved an initial R-squared value of 0.94 with an RMSE value of 0.925. Upon further optimization with additional dataset, training, and cross-validation using the MATLAB's Regression Learner App, the resultant function achieved a higher predictive power ($R^2 = 0.966$), with slope coefficient's standard error of 0.849 (and RMSE 0.902). The calibration of function 8b with optimized composite DSoB and DSuB variables achieved a marginally improved power ($R^2 = 0.975$) with a slope coefficient standard error of 0.029. Plots of the training response and fitness of the predicted versus the observed D values in the cross-validation are shown in Figure 6.

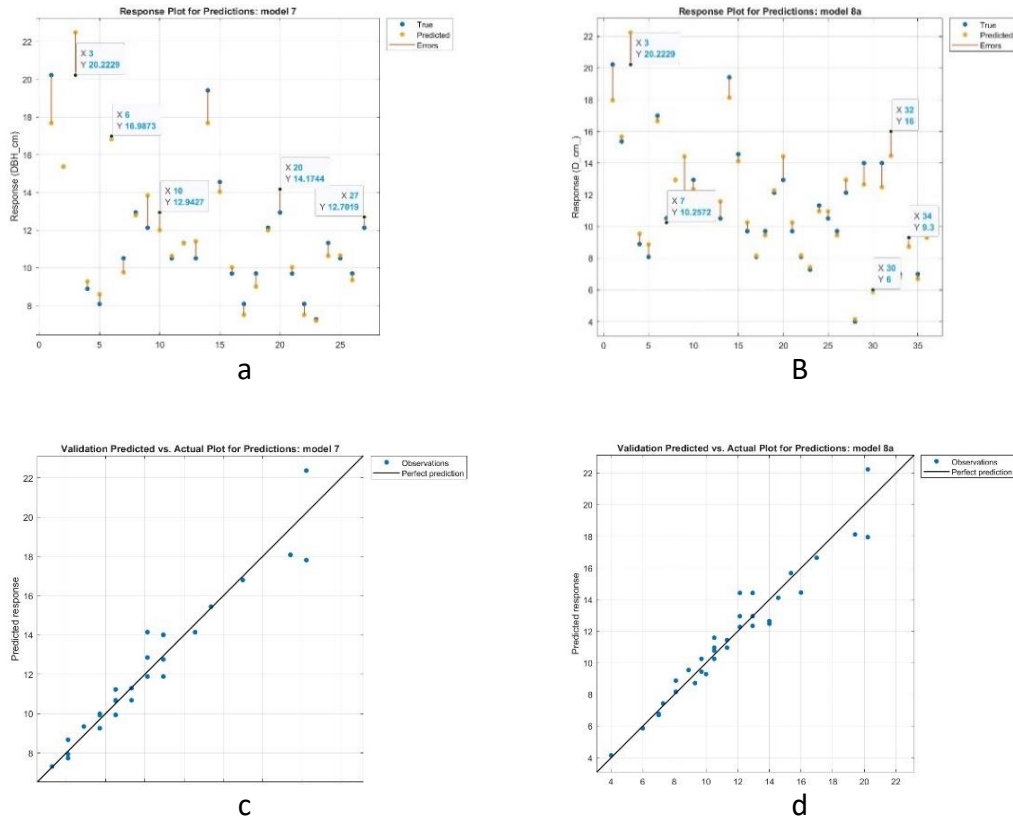


Figure 6. Response plots and scatter along the predicted trends in the training of models 7 and 8a using MATLAB's Regression Learner App

Note: The x-values shown on the data tips of Figures 5a and 5b correspond to reference points rather than inferential variables.

Table 5 summarizes the matrices and coefficients of the final models evaluated in the predictive validation tests. It includes slopes and coefficients of Models 5 and 6, which were the best-performing primary candidate models cross-validated in the machine learning process. Also shown in the table are the coefficients of models 8a and 8b, calibrated following data optimization and the machine learning cross-validation procedure using the MATLAB's Regression Learner App.

Table 5. Coefficients and metrics of the candidate models selected for validation

Model	Intercept	Slope	R ²	SE	t-value	Sig.
5	- 0.079	0.771	0.953	0.070	11.08	.001
6	0.550	0.791	0.948	0.068	11.68	.001
8a	-0.010	0.841	0.966	0.849	26.2	< 0.001
8b	0.083	0.824	0.975	0.029	28.35	< 0.001

Predictive accuracy evaluation

The RMSE values for predictive accuracy assessment of the reference and *in-situ* (local) using empirical data are shown in Table 6. The results revealed a distinct performance pattern between the external (Horvath & Popa, and Özceliket *al.*) and local models (5, 6, 8a, 8b). The performance of the Mugashaet *al.* function fell between the local and external modes, which could be expected given that it is a regional model but defined for a broad class of forests.

Table 6 RMSE values of predictive accuracy tests for the reference and the study-derived specific DS-D models

RMSE values (cm) of tests 1 - 4					
Models	Test 1	Test 2	Test 3	Test 4	Average RMSE
5	2.79	1.22	1.30	1.25	1.64
6	2.45	0.82	0.91	0.68	1.22
8a	2.50	0.812	0.85	0.74	1.23
8b	2.49	0.79	0.86	0.70	1.21
Horvath & Popa (2021)	2.85	2.14	2.59	2.10	2.42
Özceliket <i>al.</i> (2009)	2.70	1.19	1.13	1.45	1.62
Mugashaet <i>al.</i> (2021)	2.58	0.98	1.07	0.96	1.40

Note: Input for Tests 1 and 2 came from a small subset of DSoB variables taken from a single CPS stand, while input variables for Tests 3 and 4 came a randomized composite

DSoB data taken from two different ECP sampling. The test 1 subset of the data contained an outlier, which may have skewed the RMSE value of that test.

The Horvath & Popa (2021) model maintained satisfactory predictive accuracy. However, the model recorded the highest average RMSE (2.42 cm) among all models across the four evaluation tests, with values ranging from 2.10 cm – 2.85 cm. The Özcelik *et al.* (2009) model performed better, achieving an average RMSE of 1.62 cm from the four prediction tests. The model marginally outperformed *in-situ* model 5 in two prediction instances, but the other evaluated local models yielded lower RMSE than the Özcelik *et al.* model in all of the prediction instances. Mugasha *et al.* (2021) 's performance reflected its regional origin and broad category definition. The model outperformed the other two reference models with an average RMSE of 1.40 cm, but its predictive capacity was surpassed by those of local (*in-situ*) models 6, 8a, and 8b.

The local models outperformed the reference (external) functions in most prediction instances, likely due to their better alignment with the *in-situ* empirical datasets. The averaged RMSE values for the external models ranged from 1.40 cm to 2.42 cm, whereas the local functions demonstrated improved performance with RMSE values between 1.22 cm and 1.64 cm. Model 5 (based on DSoB) had a slightly higher average RMSE of 1.64 cm, making it less effective than the other local models while still outperforming the Özcelik *et al.* and Horvath and Popa models. In contrast, Model 6 (based on DSuB) demonstrated a consistently higher accuracy across all tests, achieving an average RMSE of 1.22 cm and the lowest single error (0.68 cm in Test 4) of any prediction instance. Meanwhile, models 8a (optimized using DSoB data aggregation) and 8b

(calibrated using optimized aggregation of both DSoB and DSuB datasets) achieved an average RMSE of 1.23 cm and 121 cm, respectively.

Effect sizes assessment

The charts in Figures 7a and 7b depict the effect sizes of the evaluated candidate and reference functions. The effect size computation was done by normalizing the RMSE values of the last two predictive evaluation tests and recorded as relative RMSE (RRMSE). In Figures 7a and 7b, the RRMSE values on the left were normalized by the mean of the observed (target) D values, while those on the right are normalized by the range values. Figure 6a is based on the RMSE values from the third predictive accuracy test iteration, while Figure 6b corresponds to the fourth iteration.

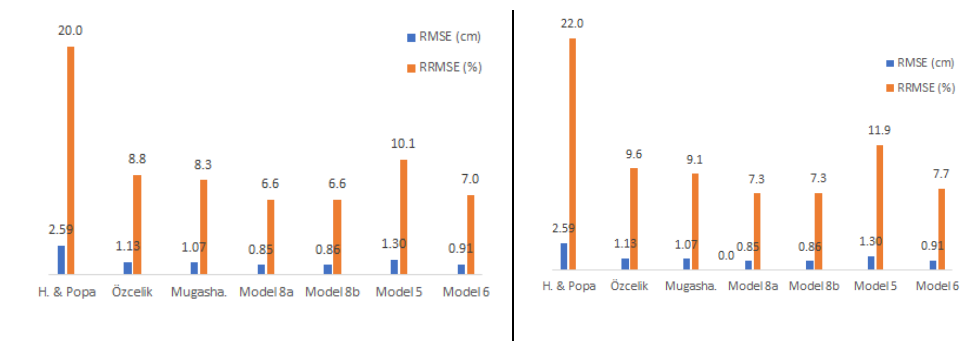


Figure 7a. RMSE (cm) and relative RMSE (RRMSE = value x 100%) normalized by mean (left) and range (right) of the observed D

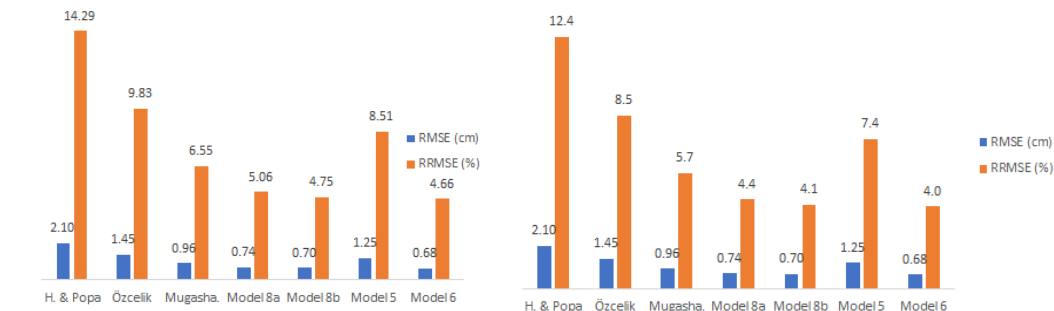


Figure 7b. RMSE (cm) and relative RMSE (RRMSE = value x 100%) normalized by mean (left) and range (right) of the observed D

The effect sizes were only slightly different between the mean normalized and range-normalized RRMSE values in the two test instances. While the mean-derived RRMSE values indicated a superior effect size of the model in the first test iteration (6a), the reverse was the case in the second evaluation. Overall, the effect sizes were generally high among the local and regional models and about the same for the external models. The Horvath and Popa model consistently had the lowest effect size across all the RRMSE computations, indicating the model's inadequate alignment with the East African ECP data. Nonetheless, the RRMSE values of the model's prediction in the ECP stands ranged from 12% to 20%, which can be considered moderate (Zhang *et al.* 2019).

All the other reference and candidate models remained within a 4% to 0.12% (RRMSE 0.4 – 0.12 cm) threshold, indicating 88% to 96% prediction accuracy rates (Zhang *et al.* 2019). In terms of comparison, however, models 8a and 8b recorded RRMSE values ranging from 4% to 7%, which represented the highest effect size among the comparative functions. This was followed by model 6 and the Mugasha *et al.* function (RRMSE = 4%–8% and 6%–9%, respectively).

DSoB vs DSuB as predictor and input variables

Figure 8 depicts the results of the comparative assessment of DSoB versus DSuB as predictors. From visual inspection, model 6 predicted values were closer to the actual D values in 73% of the observations in the first evaluation instance. Model 8b similarly outperformed model 8a in the initial assessment instance, going by the visual inspection. The results were similar in the second evaluation test, indicating that DSuB is a better predictor of D than DSoB.

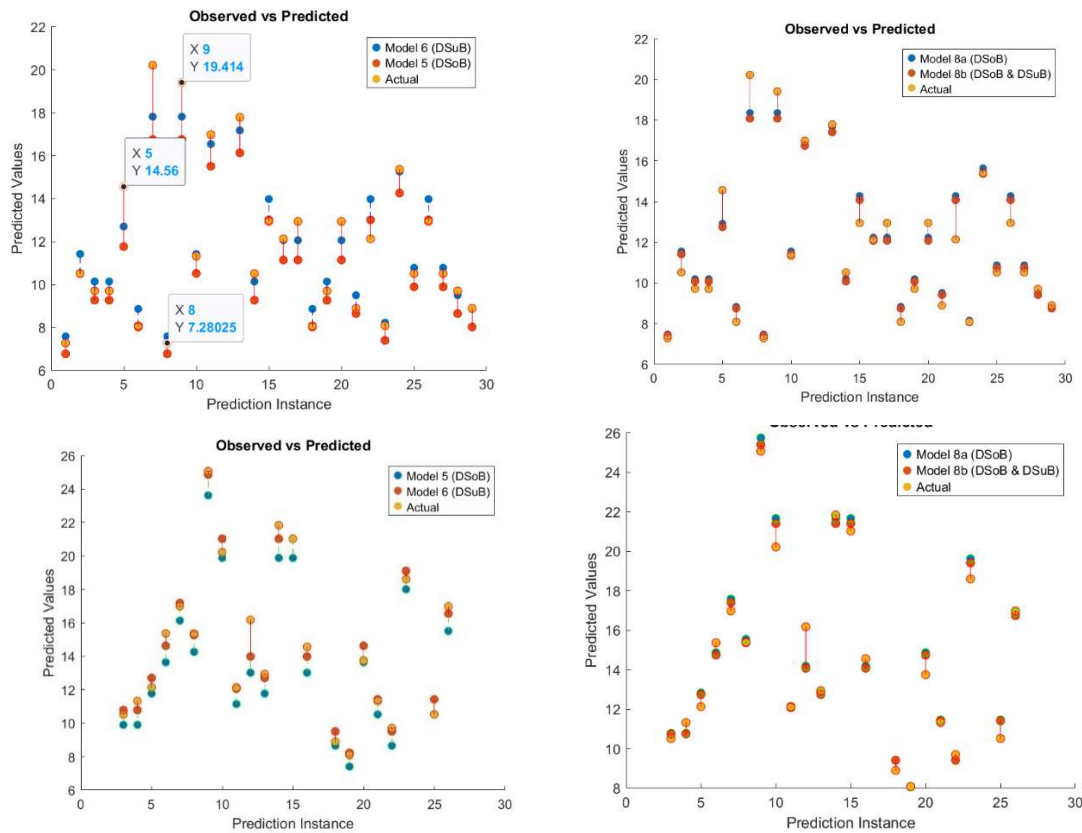


Figure 8. Scatterplots of comparative assessment of DSoB vs. DSuB as DS-D model predictor variables from two test instances using randomized datasets

Table 7 shows the error residuals in the test to compare DSoB versus DSuB as input values of DS-D models. The use of DSuB as the input variable consistently resulted in lower RMSE across all iterations when applying models 5, 6, 7, 8a, 8b, and the three reference functions. This outcome persisted even though the reference models and models 5 and 7 were originally developed using DSoB as the predictor variable. A paired-sample t-test analysis yielded p-values ranging from ≤ 0.00 to 0.02 for both one-tailed and two-tailed tests, indicating that the differences in mean values and the direction of these variations were statistically significant.

Table 7. Residuals of the predictive tests to compare DSoB versus DSuB as input values of DS-D models.

	CP stand		FR stand		FC Stand	
	Input		Input		Input	
Model	DSoB	DSuB	DSoB	DSuB	DSoB	DSuB
5.00	2.91	3.11	2.26	1.98	0.74	1.08
6.00	3.19	2.82	2.68	2.14	1.12	0.70
7.00	3.05	2.73	3.38	2.71	2.14	1.50
8a	3.48	2.84	2.79	2.25	1.14	0.73
8b	3.27	2.84	2.71	2.19	1.06	0.73
H. & Popa	4.27	3.18	4.40	3.60	3.22	2.44
Özçelikt <i>al.</i>	4.22	3.08	3.16	2.52	1.54	0.87
Mugashaet <i>al.</i>	2.94	2.95	2.42	1.98	0.89	0.78

Note: CP, FR, and CR = ECP stands in which D values were predicted

Discussion

The broad category DS-D model developed by Mugashaet *al.* (2021) for cultivated tree plantations in East Africa recorded lower error residuals in estimating D from DS in the study ECP compared to the other two reference models, which were built with data from different regions. The finding suggests that the model of Mugashaet *al.* more closely aligns with the climatic condition of the ECP source of the experimental data. It further supports the proposition that local or regional models outperform *ex-situ* derived broad category functions, highlighting the need for regional-scale generic model application, especially for species or forest types for which site- or species-specific models have not been derived.

Models 6, 8a, and 8b had identical mean RMSE values from validation tests 1 to 4 (1.22 cm, 1.23 cm, and 1.21 cm, respectively), the lowest average error margins among all candidate and reference models. The next lowest mean of RMSE was 1.40 cm recorded for the Mugashaet *al.* model in the four iteration tests. This was followed by 1.64 cm for the Özçelikt *al.* (2009) model, and 1.65 cm for candidate model 5. The In-situ models 6, 8a, and 8b outperformed all the reference models, further supporting the previous findings, which indicates a higher performance of local models (Alvarez *et al.* 2012).

These findings suggest that species- and site-specific modeling is needed for better inventory accuracies, aligning with previous research findings in the study region showing that district-level generic allometric equations by Kuyahet *al.* (2012a) overestimated aboveground biomass by 10% and belowground biomass by 40% when generalized to agricultural landscapes. In a comparative study conducted in Bangladesh, Rahman *et al.* (2021) similarly found that site- and species-specific allometric models yielded lower mean biases in AGB estimation than pan-tropical allometric equations.

Candidate models 1 and 2 exhibited limited explanatory power, as evidenced by higher p-values ($p = .004$ and $p = .003$), lower t-statistics, and elevated standard errors, indicating weak predictive performance. This outcome was unexpected given that the models were developed from destructively sampled data, which generally ensures high measurement precision due to non-reliance on bark gauges. Additionally, the DSoB and DSuB variables adhered to OLS regression

assumptions, suggesting that other factors might have contributed to the models' suboptimal performance.

One plausible explanation is the influence of clustered assemblages of non-cultivated species within the CP plots. The mixed-species dynamics likely disrupted the homogeneity expected in monocultural plantations. As noted by Pretzsch (2019), mixed-species stands tend to allow more unrestrained crown expansion, contrasting with the uniform competition in monocultures. Similarly, spacing adjustments in monocultures can influence canopy structure and growth uniformity (Hakamada *et al.*, 2015).

Nardini *et al.* (2021), for instance, found that denser *Eucalyptus grandis* stands (2.0×1.5 m) improved radiation use efficiency, enhancing photosynthesis and biomass. Although our experimental CP stand had wider spacing (2.5×2.5 m), less stringent undergrowth management likely facilitated the emergence of interspersed vegetation, including native species from the adjacent natural forest and agricultural field colonizers. This increased variability in canopy dynamics induced heterogeneity in growth patterns. The emergent variability in tree diameter classes could have influenced wood-bark ratios, complicating allometric model development. This aligns with Neumann & Lawes (2021a), who reported an inverse relationship between bark thickness and stem diameter. The persisting uncertainty in this area highlights the need for additional research into how mixed-species dynamics and clustered assemblages affect canopy competition, biomass, and DS-D-bark relationships in monocultural plantations.

Models 3 and 4 were not included in the validation tests, given their moderate explanatory power (67% and 66%, respectively) and inadequate conformity of their residuals to the OLS assumptions. However, the linearity of DS and D in the FR stand (from which the models were derived) appeared well established, given that the statistical procedure to remedy the outlier effect in the model parameters did not significantly change the models' effectiveness. The two models, therefore, provide a general trend line, which can be refit with additional data in a further study and validated for D and volume estimation in post-fire ECPs. This is crucial, given that we found no suitable previous DS-D model in the literature, specifically for post-fire tree plantation scenario, with which to compare models 3 and 4.

Limited insights from the two models show that significant post-fire recovery of tropical ECPs can spontaneously occur within a decade. The finding supports the recent research indicating that tree recovery can occur within a crucial two-and-a-half-year timeframe despite forest fire impact on soil chemical properties, extracellular enzyme production, and microbial balance (Schill *et al.*, 2023). However, studies from other regions on post-fire recovery scenarios suggest that trees may take several decades to return to pre-fire conditions (Rozak & Setiadi, 2016).

Significantly, Hood *et al.* (2018) noted that the underlying mechanisms for post-fire recovery remain poorly understood, given that the current mortality prediction—developed from small, regional datasets—varies widely in inputs, making comparisons difficult. To improve understanding and prediction accuracy, researchers recommend a dual approach: refining

empirical models and conducting physiological research on the underlying mechanisms of fire-induced tree mortality (Hood *et al.*, 2018). Models 3 and 4 provide a basis for such future research post-fire monocultural tree plantations.

Model 6 could better serve where the bark layer of stump is missing or where the DSuB can be accurately measured and applied as input variables without extra effort. The loss of the bark layer of stumps of logged trees may occur for several reasons, such as microbial degradation or mechanical extraction for fuel and medicinal use (Figure 1). Jones *et al.* (2020) reported that the bark component decomposed faster than wood under microbial and weathering effects despite the latter's higher composition of defensive compounds. Given the lower susceptibility of the wood segment of the stump than the bark, DSuB is often available for measurement where DSoB is inaccessible (Kozak & Omule 1992). Additional studies may, however, be necessary in this area as, more recently, Ristinmaa *et al.* (2023) found a lower rate of carbohydrate metabolism in bark than expected.

The application of DSuB as the input variable consistently resulted in lower RMSE values (compared to using DSoB as the input variable) in all iterations using the optimized model (equation 8) and the reference models. The significant p-value of the pairwise mean comparisons indicates that DSuB is a more effective predictor of DS, even when the deployed DS-D models were parametrized with DSoB as the regressors. Further research is, however, required to validate this finding under more homogenized plantation outlook than the CP and FR stands from

which we derived empirical data for the comparative assessment of DSoB versus DSuB as input variables. Such further assessment is particularly important, given that we found no similar study in the literature to compare our results.

In summary, the study demonstrated a positive correlation between DS and D across all sampling strata of ECPs, with all candidate models showing statistically significant p-values. Among these models, candidate functions 5 through 8b, which met *all* OLS regression assumptions, showed higher predictive accuracies. Model 6, based on DSuB only; model 8a, optimized by DSoB data aggregation; and model 8b, calibrated with combined DSoB and DSuB data, yielded the lowest RMSE values in all the validation tests, indicating their superior reliability and repeatability of prediction accuracy.

The performance of the reference models varied by closeness to the experimental forest type, climate, and ecological conditions in the study area. The Mugashaet *al.* (2021) model, developed with data from East Africa with similar climatic to experimental area, yielded the lowest residuals (among reference equations) in both validation instances. The Horvath A & Popa A, 2021, which was derived for broad forest classes from a more distinct ecosystem recorded the largest error values. The Özcelik *et al.* model, species-specifically defined for monocultural Brutian pine forest, recorded a mean RMSE of 1.62 cm, similar to the error margin of *in-situ* model 5. This finding supports the importance of regional, specific, and ecological contexts in allometric model selection for optimal accuracy.

The effect size evaluation (Figures 6a and 6b) using RRMSE normalized by both the mean and range of the observed D provided complementary perspectives by highlighting what the model errors mean in terms of percentages stand biomass and C. Slight differences were observed between mean- and range-normalized RRMSE values across iterations; however, local models generally exhibited higher effect sizes. Most local models, including the region-level Mugasha *et al.* model, achieved RRMSE values below 10% in nearly all predictive instances. This finding underscores the importance of tailoring predictive allometric functions to local datasets to enhance accuracy. In contrast, the Horvath and Popa model consistently displayed the lowest effect size, reflecting its *ex-situ* origin and broad-category purposes. Despite its comparatively lower effect sizes, the model maintained good to moderate levels of predictive accuracy in this study (RRMSE = 12% to 22%). In general terms, model accuracy is considered excellent when RRMSE <10%; good if $\geq 10\%$ to <20%; fair if $\geq 20\%$ to <30%; and poor $\geq 30\%$ (Jamieson *et al.*, 1991; Li *et al.*, 2013; Zhang *et al.*, 2019). The moderate to good performance of the reference models suggests the usefulness and potential reliance on external or broad category models in specific, limited scenarios.

Conclusion

In the predictive performance to tests, models 6, 8a, and 8b model as well as the Mugasha *et al.* (2021) function outperformed the Özcelik *et al.* (2009) and the Horvath & Popa (2021) models. The finding suggests that local and regional models are more effective than other *ex-situ* data-fitted generic equations. Among the regional models, the comparative effect size assessment

(Figures 6a and 6b) showed that species-specific models 6, 8a, and 8b marginally outperformed the Mugasha *et al.* model defined for the broad class of (cultivated) tree plantations. The findings support the previous research assumption that species-specific models will likely provide estimates with a lower error margin than broad-category local models (Mulatu *et al.*, 2024). Based on the study datasets, models based on DSuB also consistently outperformed those built using DSoB as the predictor variable. At the same time, the use of DSuB versus DSoB as input variables resulted in similar—and sometimes lower—error margins, even where the deployed models relied on the latter as predictor variables.

Based on the study findings, we conclude that:

- 1- Inferences can be drawn using D estimation models 6, 8a, and 8b, which exhibit an inherent error of less than 10% of the target mean D for ECP stands in growth conditions similar to those of lowland Kenya. Deploying these models offers cost-effectiveness and convenience for biomass and C accounting, which is increasingly critical in sub-Saharan Africa. Foreign market demand has driven frequent clear-cut harvesting in the region, often under loose regulatory systems. Under the prevailing practices, private forest growers sometimes bulk-sell entire mature stands to timber middlemen or women based on rough volume estimates rather than precise measurements, with record-keeping for ecosystem services or C accounting often being a low priority. These scenarios heighten the likelihood of missing D data, underscoring the practicality of DS-D models in reconstructing weight variables for planning, policy, and sustainability purposes.
2. Model 6 is recommended for coppice regenerated ECPs and intensely managed woodlots with approximately homogeneous spacing and canopy distribution.

3. The use of DSuB as the independent variable may lead to better optimization of DS-D models than reliance on DSoB. The relationship between DSoB and D is governed by bark thickness in the stem segment of the sampled trees. Recent research findings suggest that tree species, particularly those in fire or disturbance-prone habitats, likely vary the bark thickness in the lower stem sections to vascular cambium (Gumber *et al.*, 2022; Neumann & Lawes, 2021b).
4. Our results show that DSuB is as reliable as DSoB in input variables, even with DS-D models built with DSoB as input variables. In a plurality of the test instances in the study, the error margins of DS-D model prediction were smaller with DSuB as the input variable than DSoB. DSuB is possibly also a more stable input variable given that reliance on DSoB is more likely compromised by microbial-led degradation, mechanical damage, or purposeful harvest for human use, and, depending on the ecosystem, due to bark stripping by large herbivores (Konôpka *et al.*, 2022). It is unlikely for the dimensions of DSoB to be intact for measurement, whereas those for DSuB are not. DSuB is, therefore, practically and intuitively a more robust predictor of D than DSoB in the context of DS-D models, owing to its reliability, lower susceptibility to degradation or damage, and consistently smaller error margins in predictive applications.
5. Recalibration of models 3 and 4 with a robust dataset would be a good starting point for modeling vegetation recovery in forest plantations spontaneously reestablished after fire disturbance. Research gaps remain in this area, given the limited number of models to predict vegetation, biomass, and C recovery in post-fire forests (Rozak & Setiadi, 2016). Fire has been singled out as the number one risk and discouraging factor to forest

expansion through investment in commercial tree plantations (Andrew,2022).Modeling biomass growth after fire recovery may provide vital information to strengthen decision-making about new investments in short-rotation tree plantations.

6. Our study-defined models may be validated with local dataset for D estimation in other monocultural tree plantations, for tree species with resource allocation ratios similar to *Eucalyptus camaldulensis*, or in ECPs located in different regions.

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