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Modelling Height-Diameter Allometry of *Tectona grandis* under Varying Site Quality in Tanzania

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Abstract

Single tree parameters, such as tree height (H) and diameter at breast height (D), are essential for the prediction of difficult-to-measure parameters, such as volume and biomass, which are critical for yield prediction and forest management planning. Yet direct H measurement is often demanding and challenging. While various H-D models have been developed, there is insufficient information on how site quality influences H-D allometry. This study developed generalized and site-quality-specific H-D models for *Tectona grandis* (teak) plantations in Longuza and Mtibwa forest plantations, Tanzania, using a large dataset comprising 7253 observations. The dataset was separated by site class (quality) using dominant height and stand age. Models were fitted using two commonly used nonlinear model forms, *i.e.*, the Weibull and Richards. The general H-D models included site classes as random effects. The model performance was assessed using goodness-of-fit statistics, bias, and repeated random holdout validation. Findings showed that site quality strongly influenced H-D allometry, with distinct model trajectories and asymptotic H values across site classes. Although the generalised mixed-effects model improved performance relative to the fixed-effects model, it exhibited increased bias at the extremes of site quality (site class I and III). In contrast, site-quality-specific models consistently produced lower bias when applied to their corresponding site classes. These findings demonstrate that having H-D models by site quality improves H prediction accuracy. It is recommended that site-quality-specific H-D models be used in operational inventories where site class information is available, while the general model provides a robust alternative for data-limited or preliminary assessments.

Keywords

Site Quality, Site Indices, Height-Diameter Allometry, *Tectona grandis*, Mixed Effect Modelling

1. Introduction

Forest plantations have increasingly become a cornerstone of Tanzania's forestry sector, serving as a major source of industrial wood while supporting environmental protection and sustainable land management objectives. By supplying timber and other wood products, plantations have eased the harvesting pressure on natural forests and, at the same time, generate employment and income opportunities, particularly for rural populations engaged in tree growing, processing, and trade [1]. Recent assessments indicate that Tanzania hosts about 500,000 ha of forest plantations, the majority of which are owned and managed by smallholder growers and private investors, highlighting the growing importance of non-state actors in commercial forestry development [2]. Within this plantation estate, *Tectona grandis*, commonly known as teak, stands out as one of the most economically important timber species due to its high market value, favourable wood properties, and strong demand in both domestic and international markets.

Given the substantial contribution of teak to the livelihoods of individuals who are directly and indirectly engaged along the teak value chain, as well as its importance to the national economy, effective management of teak plantations is essential to ensure sustained productivity and long-term sustainability. A central component of plantation management is the accurate estimation of yield, which provides a critical basis for assessing productivity, planning harvests, and guiding the sale and purchase of teak products, particularly timber [3]. Yield estimation is commonly derived from volume, a key parameter that also enables the calculation of growth indicators such as Mean Annual Increment. At the tree level, volume is typically estimated using allometric equations that relate volume to easily measurable tree attributes, most notably diameter at breast height (D) and total tree height (H). This is because these single-tree parameters are highly correlated with tree volume [4]. In Tanzania, volume estimation equations for teak plantations have recently been developed [5], providing an important foundation for improved yield assessment and management decision-making.

From the structural form of volume allometric equations, D and H exhibit nonlinear relationships with tree volume. In general, the explanatory power of these variables increases from D to H, such that volume can be reliably estimated using D alone or through a combination of D and H [6]. However, exceptions have been reported in some monocotyledonous species, such as coconut palms, where H is a stronger predictor of volume than D [7]. For trees, however, where D has been reported to be a stronger regressor, the addition of H has been proven to add value to the volume model fit [8]. This is because the H-D ratio is not constant across different tree sizes due to variations in factors such as tree taper and crown mass fraction, making H an essential covariate in the volume and biomass models.

The application of volume allometric equations relies heavily on accurate measurements of D and H. However, measuring H is labour-intensive and time-consuming, particularly in tropical forest environments. Field conditions often further complicate H measurements, including rugged or steep terrain, large and overlapping tree crowns, obstructed visibility of tree tops due to dense canopies, and the presence of leaning or irregularly shaped trees, all of which increase measurement difficulty and potential error [9]. Consequently, the equations relating the H and D are often developed to assist in estimating H. As previously mentioned, H-D allometry is intended to explain variation in H across tree sizes. However, when trees with relatively similar D exhibit significantly different H, the integrity of the H-D relationship is compromised. In an even-aged stand of the same species, a crucial factor influencing the H-D relationship in this manner is site quality.

Based on site quality, each management unit within a plantation, commonly referred to as a compartment, is assigned a site index that reflects its inherent productivity. This site index is determined from the average H of the 100 largest trees within the compartment, ranked by D. The mean H calculated from this selected group of trees is referred to as the Dominant Height (DH). The DH is widely used as a robust indicator of site quality because it is relatively insensitive to stand density, thinning history, and short-term management interventions, and instead captures the site's long-term growth potential. This indicates that trees with relatively similar D can have different H depending on growth conditions, with trees in better sites being taller than those in poorer sites [10]. Therefore, in such a situation, one H-D equation for a particular species may not be adequate to capture all necessary variations associated with site quality. To resolve this, site quality has been treated as a random variable in the H-D equations and reported to improve model fit [11] [12]. Nevertheless, the trajectory of the general H-D model is a single curve which provides the mean value for each given range of D. One approach to ensure the robustness and adaptability of a single H-D model to variations in growth conditions is to incorporate site conditions as a random effect within the H-D model framework [10] [13].

The inclusion of random effects in the model induces partial pooling of group-level estimates, whereby estimates for individual random factors are shrunk toward the overall mean, resulting in more stable, less biased estimates across groups. This is advantageous when the sample size in each group is small [14]. However, when groups are fundamentally different, such as plots or compartments belonging to distinct site indices, and each group is supported by a large and well-balanced sample size, fitting separate models for each group is justified, as this approach avoids shrinkage toward a global mean and allows group-specific relationships to be estimated with high precision that would otherwise be partially obscured under a mixed-effects framework [14].

Against this background, the present study seeks to develop site-quality-specific H-D models for teak in the Longuza and Mtibwa forest plantations based on 7253 observations. In addition, the study compares these site-quality-specific models with a generalised H-D model fitted using a mixed-effects modelling approach, with the objective of identifying models that provide accurate and reliable estimates of tree H.

2. Materials and Methods

2.1. Study Sites

This study was conducted in the Longuza and Mtibwa forest plantations, both managed by the Tanzania Forest Services Agency (TFS).

Longuza, located on the eastern (windward) slopes of the Usambara Mountains along the coast, receives high precipitation that strongly favours teak growth. In contrast, Mtibwa is situated inland, far from the coast, and experiences relatively lower rainfall. Both sites are positioned on the windward sides of mountainous landscapes: Mtibwa lies east of the Mkingu Nature Reserve, while Longuza is east of the Amani Nature Reserve.

Mtibwa Forest Plantation is located inland, east of Mkingu Nature Reserve, relatively far from the coast in the Morogoro Region, on the eastern slopes of the Nguu Mountains within Mvomero District. The plantation lies between latitudes 6˚00' and 6˚10'S and longitudes 37˚40' and 37˚45'E. Teak was first introduced at Mtibwa in 1936 through an 8-acre trial plot, followed by the establishment of additional experimental plots in 1954, 1955, and 1957 at the Lusunguru block. Large-scale teak planting commenced in 1961 at the Mtibwa block. The plantation covers approximately 16,065.6 ha and, for management purposes, is subdivided into three blocks: Mtibwa (1023.6 ha), Lusunguru (2092 ha), and Pagale (12,950 ha). Teak is the dominant species, accounting for about 95% of the planted area. The area receives long rains from March to May, followed by a long dry season lasting until October. Short rains are from November to December. The average mean annual rainfall is 1217 mm. Since this is marginal for Teak growth, it is supplemented by sub-surface underground water. Temperatures are high, particularly from January to March. Mid-day temperatures vary from 14˚C to 36˚C. The soils in Mtibwa are sandy entisols and vertisols whereas in water-logged plains, inceptisol loams are more predominant [15].

Longuza Forest Plantation is located in Muheza District, Tanga Region, north-eastern Tanzania, between latitudes 4˚55' and 5˚10'S and longitudes 38˚40' and 39˚00'E, at elevations ranging from 160 to 560 m above sea level. The plantation is situated at the foothills of the eastern Usambara Mountains and is influenced by a coastal windward climatic regime, which contrasts markedly with the climatic conditions prevailing at Mtibwa. Similar to Mtibwa, teak is the principal tree species in Longuza, occupying approximately 96% of the planted area. The mean maximum temperature in the area ranges from 26˚C to 32˚C, while the mean minimum temperature ranges from 15˚C to 20˚C. The mean annual rainfall is 1548 mm with a dry spell between June and September. The area experiences short rain from October to December and long rain from March to May. The soil type in the study area are predominantly sandy clay loam. They exhibit dark reddish-brown to deep red hues, with coloration intensifying at greater depths. Soil depth is highly variable, spanning from shallow profiles of less than 20 cm to very deep profiles exceeding 120 cm [16]. The study site is shown in **Figure 1**.

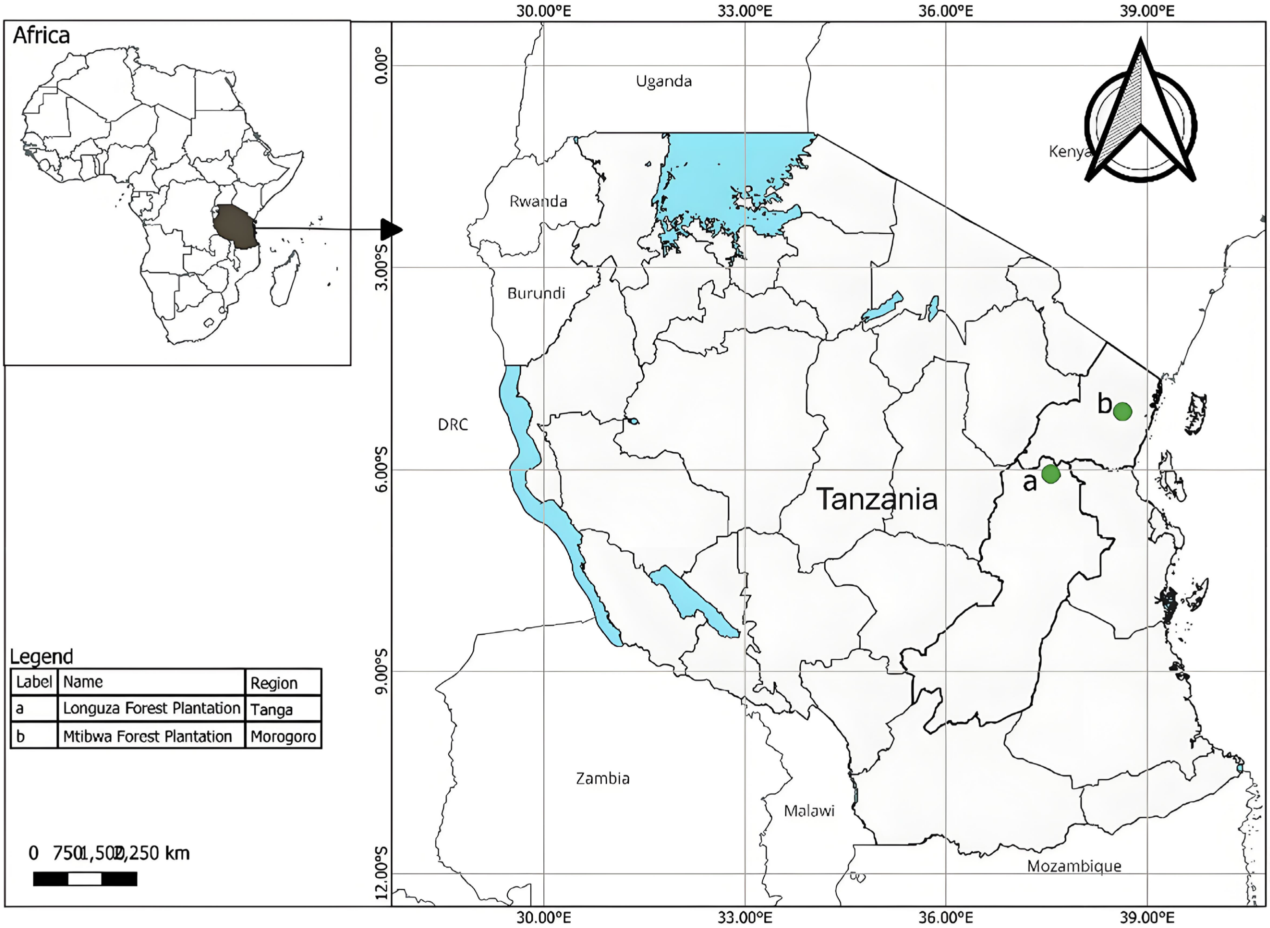

Figure 1. Study sites.

2.2. Study Design

A systematic sampling design was applied within each plantation compartment. In this study, a compartment refers to a forest plantation management unit composed of a single tree species of uniform age. This study was conducted in compartments containing stands that are at least 5 years old to generate forest inventory data for the preparation of forest management plans for Mtibwa and Longuza forest plantations. Sampling intensity was age-dependent: a 2% intensity was applied to compartments aged 5 - 12 years, while a 5% intensity was applied to compartments aged 12 years or older. Plot density varied among compartments according to compartment area and the selected sampling grid, with inter-plot spacing of 150 m × 100 m for compartments aged 5 - 12 years and 100 m × 60 m for compartments older than 12 years. All plots were circular with a radius of 9.8 m. In total, 97 teak-planted compartments were inventoried, comprising 2462 sample plots.

2.3. Data Collection

Within each sample plot, site and stand attributes were recorded, including geographic coordinates, slope, stand age, planted species, and management interventions such as pruning and thinning. Diameter at breast height (D) was measured for all trees within the plot. Tree height (H) was measured for a subset of five trees per plot. Three of these trees were selected from the largest-diameter individuals to estimate dominant height (HD), consistent with the standard practice of sampling 100 dominant trees per hectare, given the plot size of 0.03 ha [17]. The remaining two trees were selected to represent intermediate and suppressed size classes. Trees exhibiting broken tops or stem deformities were excluded from height measurements.

2.4. Data Preparation

With site classification based on stand age and the mean height of dominant (DH) trees measured at the plot level. For each plot, the observed age and mean HD were compared against site class curves derived from the yield table developed for Longuza and Mtibwa plantation [18]. The yield table defines three site classes corresponding to reference H of 18, 22 and 26 m. Each plot was assigned to the site class that minimised the absolute difference between the observed mean DH and the DH predicted by Equation (1).

$$\mathrm{HD} = 1.25 * \mathrm{RH} * \left(1 - \exp\left(-0.1013 * \mathrm{A}\right)\right)^{1.5041} \tag{1}$$

where the RH is the reference tree height, DH is the predicted dominant height, and A is age.

Once the site class of each plot was determined, three trees measured for H were selected for H-D development. This included one sample tree randomly chosen from the three largest trees, and two sample trees that did not participate in determining the site class, *i.e.*, medium, and the smallest. **Table 1** presents the descriptive statistics summary of sample trees for H-D development for each site class. The scatter plot of the D versus H of each site class is presented in **Figure 2**. In addition, a sensitivity analysis was conducted to assess the reliability of the site class allocation. This involved randomly adding or subtracting one meter to the dominant height values, assuming this to represent potential measurement error. The results showed that out of 2462 plots, only 56 plots (2.27%) were reassigned to a different site class. A realistic measurement error of ±1 m only affected a small proportion of plots, meaning that minor field measurement inaccuracies are unlikely to substantially affect site productivity classification.

Table 1. Descriptive statistics summary of sample trees.

Study site	Site class	*n*	Diameter (cm)			Total tree height (m)		
			Mean	Range	SD	Mean	Range	SD
Longuza	1	2893	21.14	2.2 - 65	9.48	19.95	2.44 - 42.98	5.17
Longuza	2	709	18.42	2.9 - 50	6.58	17.46	3.35 - 32.00	4.31
Longuza	3	158	14.01	2.6 - 34	6.28	13.02	2.44 - 24.38	5.00
Mtibwa	1	1417	18.35	2.1 - 59.4	8.22	16.62	2.44 - 30.78	5.40
Mtibwa	2	1114	18.84	2 - 53.9	8.27	15.94	1.83 - 28.04	4.86
Mtibwa	3	962	13.92	2 - 50.3	8.53	11.10	1.52 - 24.08	5.32
	All	7253	18.86	2 - 65	8.95	17.12	1.52 - 42.98	5.89

n: number of observations; SD: Standard Deviation.

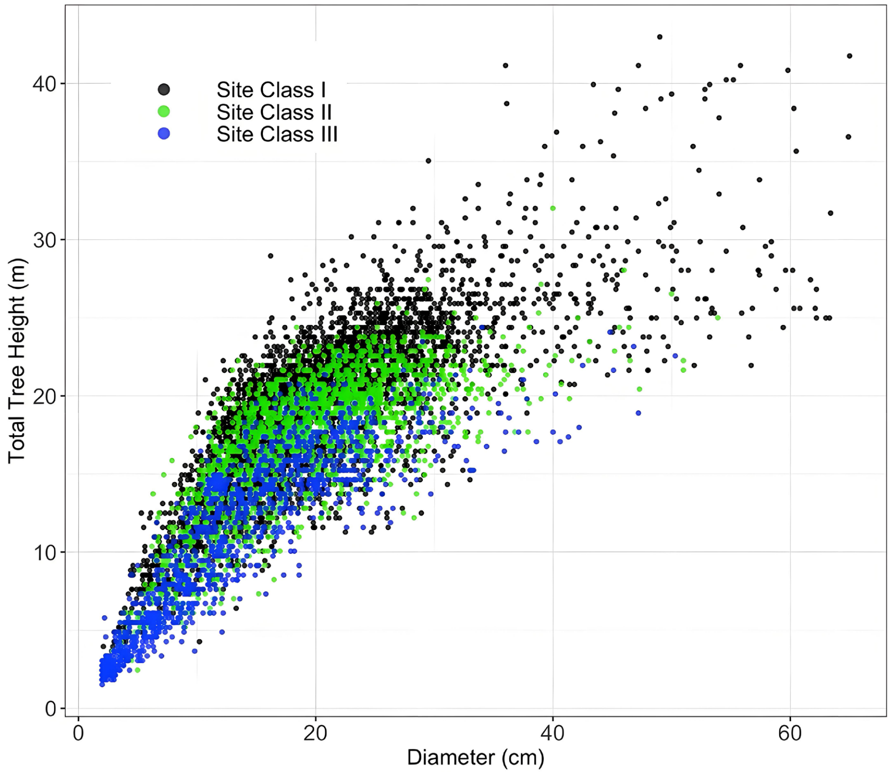

Figure 2. Scatter plot of height versus diameter.

2.5. Data Analysis

2.5.1. Fitting the H-D Models

Model development was carried out in two phases. In the first phase, a general H-D model was fitted using the pooled dataset from all site classes. In this phase, a model was developed using a nonlinear mixed-effects modelling approach, where the site classes were incorporated as a random effect, allowing key model parameters, e.g. asymptote, to vary among site classes. This approach enabled the model to capture systematic differences in H-D relationships associated with site productivity while simultaneously utilising information from the full dataset to improve parameter estimation and overall model goodness-of-fit.

Phase II involved fitting H-D models for each site class. This phase was based on the assumption that the general mixed-effects H-D model, which treated site class as a random effect, might not fully capture site class-specific H-D relationships with sufficient accuracy when predicting H for each class. By stratifying the data by site class, this approach capitalised on the relatively large sample sizes available within each class and enabled the development of site-class-specific H-D models [14].

The H-D relationships were modelled using biologically meaningful equation forms that describe tree H growth as a function of D. Numerous functional forms for H-D relationships have been documented in the literature [19] [20]. From these, two well-established nonlinear models (Equations (2) and (3)), that have been applied elsewhere and performed well, were selected for this study [21] [22].

These models were chosen for their proven flexibility and their ability to represent the sigmoidal growth pattern characteristic of tree H development, characterised by rapid H increment at smaller diameters followed by a gradual levelling off as stands mature. In these formulations, parameter β_0 determines the asymptotic maximum H approached as diameter increases, while β_1 governs the rate at which H approaches this asymptote, thereby controlling the curvature and overall shape of the H-D relationship [23].

$$\mathrm{H} = 1.3 + \beta_0 * \left(1 - \exp\left(-\beta_1 * \mathrm{D}^{\beta_2}\right)\right) \tag{2}$$

$$\mathrm{H} = 1.3 + \beta_0 * \left(1 - \exp\left(-\beta_1 * \mathrm{D}\right)\right)^{\beta_2} \tag{3}$$

where $\beta's$ are model parameters to be estimated.

When fitting the generalised H-D models, the random effects were allowed to vary across the parameters β_0 and/or β_1. The parameters β_0 and β_1 were expressed as β_0 + S_0 and β_1 + S_i, respectively, where $S's$ expresses the difference of parameter β_0 and β_1 of site class *i* from the mean value obtained from Equations (2) or (3) or the typical site class. All H-D models were fitted using *nlme* package in R software [24]. The random functions in the *nlme* package were not enabled when fitting site-class-specific models. In both modelling approaches, a power variance function (*VarPower*) was applied to account for heteroscedasticity in the residuals [25]. Models' performance was evaluated using root mean square error (SE), coefficient of determination (R^2), mean prediction error (PE%, Equation (4)), and the Akaike Information Criterion (AIC). Although all metrics were considered to assess goodness of fit and predictive accuracy, final model selection was primarily based on the model with the lowest AIC. The significance of PE% was further assessed using a paired t-test, comparing the observed H and the estimated H.

$$\mathrm{PE\%} = \left(100 \times \sum_{i=1}^{n} \left(\frac{H_i - \hat{H}_i}{H_i}\right)\right) \Big/ n \tag{4}$$

where PE% is the mean prediction error percentage, H_i is the observed value of total tree height for observation *i*, $\hat{H}_i$ is the predicted value of total tree height for observation *i*.

2.5.2. Validation of the Selected Models

Model validation was conducted using a repeated-random holdout approach. For each iteration, 80% of the observations were randomly assigned to the training dataset for model calibration, while the remaining 20% were reserved for independent validation [26]. This validation procedure was applied consistently to both the generalised H-D models and the site class-specific H-D models. To reduce the influence of random partitioning and ensure stable validation results, the resampling process was repeated 50 times. Performance metrics, including the mean standard error percentage $\left(\mathrm{SE\%} = 100 * \frac{\mathrm{SE}}{\bar{\mathrm{H}}}\right)$ and the PE%, were averaged across all iterations, and the corresponding confidence intervals were computed to quantify uncertainty and assess model reliability.

3. Results

3.1. Height-Diameter Model Performance

The performance of the fitted H-D models is presented in Table 2. For the general H-D equations, the R^2 ranged from 0.71 to 0.77, while SE varied between 2.83 and 3.16. The mixed-effects general model exhibited a higher R^2 (0.76 and 0.77) and lower SE (2.83) than the corresponding fixed-effects model ($R^2 = 0.71$; SE = 3.15). Incorporating site index as a random effect improved model fit relative to the non-mixed model, as evidenced by a lower AIC value. Among the two model forms evaluated (Equations (2) and (3)), Equation (3) fitted with mixed effects was selected as the best-performing general H-D model. None of the PE% values were significantly different from zero ($p > 0.05$) in all cases.

For the site-quality-specific models, the R^2 ranged from 0.70 for site classes I and II to 0.81 for site class III. The SE for site classes I and III were identical across the competing models; however, for site class II, Model 2 exhibited a lower SE. In addition, PE% values were consistently low compared with the general H-D models and were not significantly different from zero ($p > 0.05$). Consequently, Model 2 was selected for site classes I and II, and Model 3 for site class III. Model expressions of the selected model are presented in Equations (5) to (8).

The patterns of the selected H-D models' curves, along with the site-class scatter plots, are shown in Figure 3. As expected, the model's asymptotic values increased with improving site quality. The estimated asymptotic H values were 27.4 m for site class I, 20.4 m for site class II, and 16.9 m for site class III. The selected general H-D model yielded an estimated asymptotic H of 23.4 m, which was well below site classes I and II but higher than site class III. The residual plots of the selected H-D models are shown in Figure 4. The residual plots for all selected models did not indicate any bias.

Table 2. Performance of the fitted H-D models.

Type	Model #	Performance criterion			
		SE	R^2	AIC	PE
General	2	3.16	0.71	36670	−4.45
	2 (Mixed effect)	2.83	0.76	35732	−4.47
General	3	3.15	0.71	36613	−4.23
	3 (Mixed effect)	**2.83**	**0.77**	**35717**	**−4.24**
Site Class I	2	3.05	0.70	21683	−2.09
	3	**3.05**	**0.70**	**21577**	**−3.07**
Site Class II	2	2.58	0.70	8660	−3.71
	3	**3.05**	**0.70**	**8654**	**−3.46**
Site Class III	2	**2.16**	**0.83**	**4776**	**−1.95**
	3	2.16	0.83	4781	−1.90

$$H_{\text{Site I}} = 1.3 + 27.4321 * \left(1 - \exp\left(-0.0638 * D\right)\right)^{1.1892} \quad (5)$$

Standard error of parameters in their order: 0.4803; 0.0017; and 0.0221

$$H_{\text{Site II}} = 1.3 + 20.4472 * \left(1 - \exp\left(-0.1205 * D\right)\right)^{1.8987} \quad (6)$$

Standard error of parameters in their order: 0.2493; 0.0031; and 0.0474

$$H_{\text{Site III}} = 1.3 + \left(16.9763\right) * \left(1 - \exp\left(-0.0185 * D^{1.5494}\right)\right) \quad (7)$$

Standard error of parameters in their order: 0.2493; 0.0031; and 0.0474

$$H_{\text{General}} = 1.3 + \left(24.0209\right) * \left(1 - \exp\left(-0.0897 * D\right)\right)^{1.6231} \quad (8)$$

Standard error of parameters in their order: 0.2280; 0.0025; and 0.0388.

Variance component of the random effect: variance of the asymptote parameter $3.209973*10^{-8}$; STD = 0.00018; variance of Residual = 0.083.

3.2. Validation of the Selected Height-Diameter Models

The validation results for the selected H-D models are presented in Table 3. For the general H-D models, both the SE% and the PE% exhibited a clear dependence on site quality. Model performance was strongest in site class II, while reduced accuracy was observed in both site class I and site class III. Across the site classes, SE% values ranged from 15.89% to 25.49%, whereas PE% varied from −3.01% to −25.47%. These results indicate that the general H-D model provides relatively accurate height predictions under moderate site conditions but performs poorly at the extremes of site quality, where prediction uncertainty and bias increase substantially.

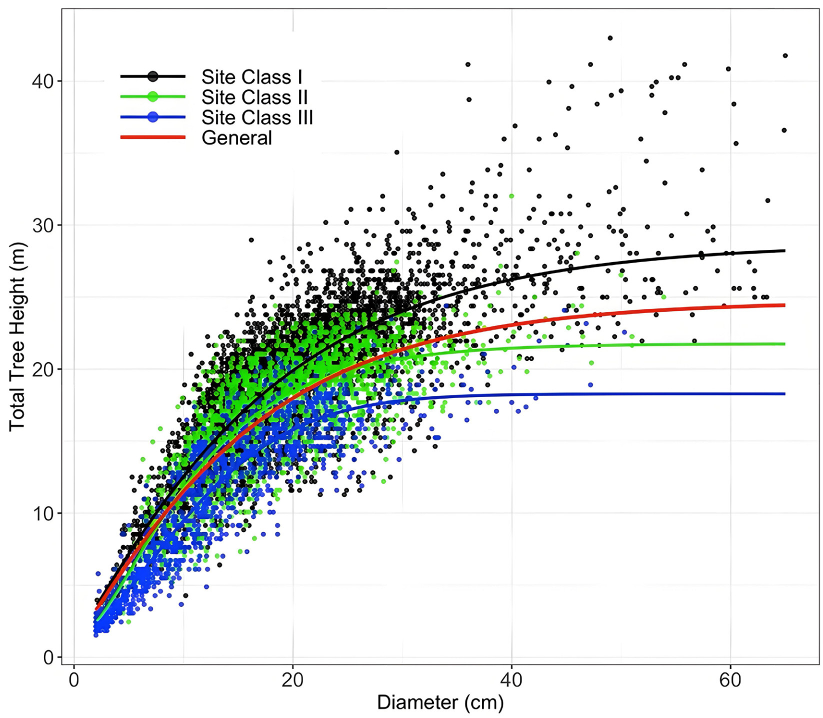

Figure 3. Site classes' scatter plots and the curves of the selected site classes and general H-D models.

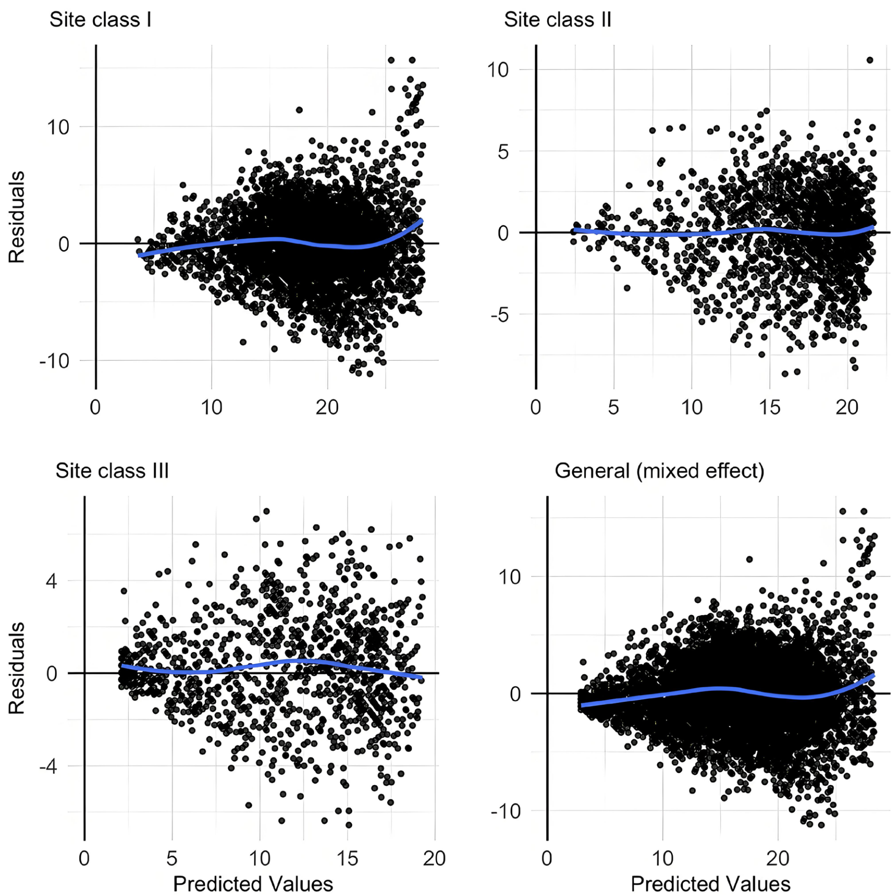

Figure 4. Residual plots of the selected H-D models.

This pattern is further illustrated in **Figure 5**, which shows the distribution of PE% across validation iterations for each site class when applying the site quality-specific models. The PE% remains relatively stable and near zero, indicating consistent and unbiased model performance when applying the site class specific models. In contrast, PE% increases progressively as site quality deviates from site class II, either toward higher or lower site classes, with the largest deviations observed in site class III when applying the general H-D models. This trend highlights the reduced reliability of the general H-D model under site conditions that depart from moderate site quality. When assessing the model on the whole data set, the SE% and PE% were found to be lower.

The site-specific H-D models consistently exhibited stable, superior performance across all site classes. The SE% values remained within a narrow range of 15.62% to 17.32%, while the PE% ranged from −3.39% to −3.83%, indicating minimal bias when the site quality-specific model is applied to the corresponding site quality. This stability is also evident in **Figure 5**, where the magnitude and spread of PE% across validation iterations are comparatively small and uniform for the site-specific models. Overall, these findings highlight the advantage of using site-specific H-D models, as they substantially reduce prediction error and bias and provide more reliable height estimates across varying site conditions.

Table 3. Validation results showing the standard errors and mean prediction errors of selected models, tested on independent data.

Model type	Site class	SE% ± CI*	PE% ± CI*
General	1	19.26 ± 0.19	−6.75 ± 0.17
	2	15.89 ± 0.16	−3.01 ± 0.29
	3	25.49 ± 0.32	−25.47 ± 0.51
Overall		18.98 ± 0.17	−6.43 ± 0.71
Site quality specific	1	16.19 ± 0.13	−3.42 ± 0.21
	2	15.62 ± 0.17	−3.39 ± 0.31
	3	17.32 ± 0.23	−3.83 ± 0.43

* *CI*: Confidence Interval of the mean value.

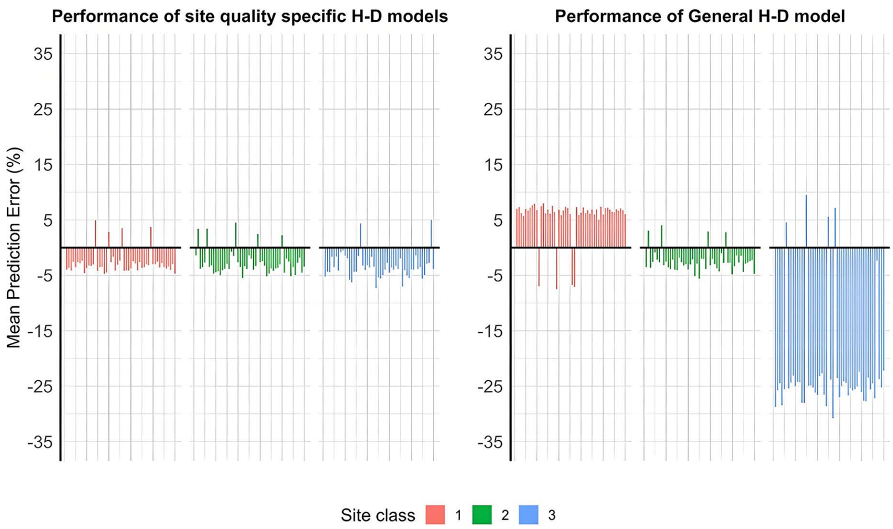

Figure 5. The pattern of the prediction error percentage across the validation iterations.

4. Discussion

This study was conducted at two sites. Longuza, located on the eastern (windward) slopes of the Usambara Mountains along the coast, receives high precipitation that strongly favours teak growth. In contrast, Mtibwa is situated inland, far from the coast, and experiences relatively lower rainfall. Both sites are positioned on the windward sides of mountainous landscapes: Mtibwa lies east of the Mkingu Nature Reserve, while Longuza is east of the Amani Nature Reserve. Together, these contrasting site conditions provide a strong foundation for assessing the influence of site quality on H-D allometry. Moreover, the study utilized comprehensive dataset comprising measurements from 97 teak-planted compartments, 2462 sample plots, and a total of 7253 observations. All site classes were well represented, with a minimum of 158 observations, *i.e.*, 158 for site class III, 709 for site class II, and 2893 for site class I. Such a large dataset provides an empirical basis for modelling the effects of site quality on H-D allometry. In contrast, earlier studies on teak H-D relationships in Tanzania relied on smaller datasets, often with fewer than 92 observations per site when developing general H-D models [5].

The developed general H-D model, which included site indices as random effects, outperformed the general models with only fixed effects across all performance criteria. This improvement is likely attributable to the mixed-effects framework's ability to capture site-quality variability that cannot be adequately represented by fixed effects alone [27]. The R^2 was comparable to other studies [13] but slightly lower than other studies [12]. A slightly lower R^2 in this study could be attributed to the larger, more heterogeneous dataset, which encompasses a wider range of site qualities, stand structures, and environmental conditions and typically increases variability [12] [19].

Comparing the performance of the general and site-specific models, the findings show that R^2 and SE were slightly higher and lower, respectively, for the general than for the site-specific models. The observed differences likely reflect data structure and sample size effects rather than a clear superiority of the general models, reinforcing the need to interpret R^2 and SE alongside bias-based metrics and model applicability. In addition, when comparing models fitted to different datasets, differences in R^2 may simply reflect differences in data spread rather than differences in model quality [28]. Since the selection of the model to apply relies on the magnitude of bias, among other factors, the site-quality-specific model demonstrated lower PE% than the general H-D model, although all the selected models' values were not different from zero.

Separating the dataset by site class proved effective, as each group exhibited distinct H-D allometry. This finding aligns with the well-established principle that site quality systematically shifts H-D relationships by altering resource availability, climate conditions, and stand structure, which collectively influence H growth. The distinct H-D allometry patterns observed across site classes are reflected in the asymptotic H parameter, which increased consistently with site quality, a pattern widely documented in the literature and mechanistically linked to higher water availability, nutrient status, and favourable growing conditions on productive sites. [20] demonstrated that mean annual precipitation and basal area substantially improved H-D model fits in Tanzanian forests, with mean tree height increasing proportionally with precipitation, while others reported similar climate-driven variation in H-D exponents across multiple sites in China [13].

Although the general H-D model incorporating site indices as random effects performed better than the general model with only fixed effects, consistent with the advantages of mixed-effects approaches documented [29], it still did not surpass the performance of the site-quality-specific models. This result reflects the fact that each site possesses its own unique H-D allometry. This implies that when abundant local H measurements are available, and strong site peculiarities occur, fully site-specific models can provide marginally superior fits to generalised mixed-effects models, though the latter offer an excellent trade-off between accuracy and measurement effort when calibrated with even small local samples [29].

The validation results show that, for the selected general H-D model at each site, PE% was less than 6% for site classes I and II and 25% for site class III. This indicates that the general H-D model performed relatively well for site classes I and II, which had large numbers of modelling observations (709 and 2893, respectively), compared to site class III (158 observations). This implies that, although mixed-effects models reduce bias associated with unequal group sizes through partial pooling, groups with larger numbers of observations could still exert greater influence on model fitting because their random effects estimates are less strongly shrunk toward the overall mean [27]. Application of the site-specific model resulted in a lower PE%. This signifies that the site quality often changes the H-D asymptote H, and therefore signifies that one parameterisation cannot fit all site classes without bias [30]. However, when tested on the entire dataset, the general H-D model yielded a lower PE%, mainly due to error cancellation [10] [31].

The site-quality-specific H-D models developed in this study are directly applicable to forest inventory, yield estimation, and management planning in Tanzanian teak plantations, particularly where direct H measurement is limited by time, cost, or operational constraints. By accounting for site productivity differences, these models reduce the bias associated with applying a single generalised H-D model across heterogeneous site conditions. When models are combined with existing volume equations, they are expected to improve estimates of tree and stand volume, growth, and harvestable yield, since all these stand variables are highly correlated with H.

5. Conclusion

This study developed generalized and site-quality-specific H-D models for teak plantations using data collected from Longuza and Mtibwa. The findings demonstrated that site quality strongly influences H-D allometry, resulting in distinct model forms across site classes. Although the generalised mixed-effects model improved performance relative to fixed-effects models, site-quality-specific models consistently produced lower PE% and more stable estimates when applied to their respective site classes. It is therefore recommended that site-quality-specific H-D models be used as the standard approach when site-class information and sufficient data are available, as they improve the accuracy of H, volume, and yield estimates for management and planning. The generalised mixed-effects model can serve as a robust alternative in data-limited situations. Future work should focus on integrating these models into growth and yield systems and testing their applicability in other teak-growing regions.

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Conflicts of Interest

The authors declare no competing interests.

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