

Research Article

Height-Diameter Modeling of *Cinnamomum tamala* Grown in Natural Forest in Mid-Hill of Nepal

Mukti Ram Subedi ¹, Bishwa Nath Oli,² Surendra Shrestha,³ and Sophan Chhin¹

¹Forest Resources Management Program, Division of Forestry and Natural Resources, West Virginia University, Morgantown, WV, USA

²Ministry of Forests and Environment, Kathmandu, Nepal

³Graduate School of Geography, Clark University, Worcester, MA, USA

Correspondence should be addressed to Mukti Ram Subedi; mrs0070@mix.wvu.edu

Received 14 May 2018; Revised 9 September 2018; Accepted 10 October 2018; Published 28 November 2018

Academic Editor: Scott D. Roberts

Copyright © 2018 Mukti Ram Subedi et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Tree height (H) and diameter at breast height (D) are key variables to calculate tree volume and biomass. We developed a height-diameter (H-D) model for *Cinnamomum tamala* by evaluating 18 nonlinear models. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), mean bias, Mean Absolute Error (MAE), graphical appearance, and biological logic were the criteria used to evaluate the predictive performance of the models. Gompertz model (M14) performed the best for predicting the total height of *C. tamala* trees with the least RMSE (1.742 m), mean bias (0.012 m), and MAE (1.342 m) and satisfied model assumptions and biological logic. Validation data ranked the Gompertz model as the best model with RMSE (1.546 m), mean bias (-0.106 m), and MAE (1.149 m). Despite the consistent performance of the Gompertz model, it tended to underestimate the height prediction for taller (dominant crown class) and larger trees. Further work on refitting and validation of the proposed model with data from a larger geographic area, wider-ranging sites, and stand conditions is recommended.

1. Introduction

Tree height (H) and diameter at breast height (D) are fundamental variables in most forest inventories which are required to calculate tree volume, biomass, carbon storage, and survival analysis [1–4]. Accurate in situ measurement of D is easy and cost-effective. However, height measurement is labor-intensive, time-consuming, expensive, and prone to observational and measurement errors [5, 6]. Predicting forest dynamics through growth and yield simulation also requires individual tree level information, such as H and D. A height-diameter (H-D) relationship model can be easily built when both H and D variables are measured. The model then can be used to estimate missing tree height, biomass production, and stand dynamics.

The allometric equation [7] serves as a tool to relate easily measurable morphometric variables (e.g., D) to the total height of the tree. Conventionally, H-D relationship models have been developed and applied to pure even-aged

stands or plantations using D as a predictor variable [1, 2]. Recent studies employ other stand attributes (e.g., site quality, stand age, stand density, and dominant height) in mixed-effect H-D relationship models [8–13]. In mixed effects H-D relationship models, population-averaged (fixed parameters common to population), as well as subject-specific effects as random effects, are allowed. Mixed-effect H-D relationship models improve accuracy over nonlinear models that are based on the minimization of sums of squares.

Generally, the site-specific H-D relationship models that are developed as H-D relationship can vary with differences in age, site quality, competition, stand age, and silvicultural treatment applied [14–17]. Although stand specific H-D relationship models are labor-intensive, costly, and time-intensive, these models have been proved to be more accurate in the realistic description of forest structure, growth simulations, and plot-level volume [18]. Due to a limited geographical range of natural *C. tamala* stands, cross-sectional nature of data, and for simplicity of model use, we employed

ordinary nonlinear least square equations. The model developed should be considered as a site-specific model as it was built considering fewer stands.

Cinnamomum tamala T Nees and Eberm (family Lauraceae) is a moderate-sized, evergreen, monoecious tree species distributed at 900–2000 m above sea level in the tropical and subtropical Himalayas [19]. Natural stands of *C. tamala*, being a moderate shade-tolerant species [20], are mostly found in shady-moist sites and grow well under full illumination. *C. tamala* is native to Nepal, China, India, and Bhutan [21]. *C. tamala* trees are extensively managed, in situ and ex situ, for leaf and bark production due to dwindling natural population and high economic potentials [22]. The bark is traded to India [19] and is often used as a substitute for *Cinnamomum zeylanicum* [23]. Department of forests, Nepal [24], has prioritized *C. tamala* for research and management because *C. tamala* bark forms a significant part of national nontimber forest product trade, by both volume and economic value.

Despite receiving a priority for research and management in Nepal and conservation in India, studies on *C. tamala* forests are limited. Since bark is a highly traded product, H-D relationship model is an essential decision-making tool both for management institutions and government for estimating forest volume and above-ground biomass, growth and yield modeling, and modeling ecophysiological process-based models of forests. However, research in this direction is limited within the distribution range of *C. tamala* and has mostly focused on conservation, ethnopharmacological properties, dispersion pattern, cultivation, and harvesting practices [25–29]. In Nepal, Tree Improvement and Silviculture Component, TISC [30], and Poudel et al. [31] developed bark biomass production models in farm-grown trees and natural forests [32]. Equations for the H-D relationship for *Cinnamomum tamala* grown in the natural forest have not been reported in past studies. Tree height increases nonlinearly with stem diameter [33, 34]. Therefore, linear models are inadequate for predicting tree height [35]. In this paper, we evaluated 18 nonlinear models to develop the H-D relationship model for *C. tamala* trees. To the best of our knowledge, this is probably the first attempt to establish an H-D relationship model for natural *C. tamala* forests. Our model would be beneficial to researchers, managers, and academicians within the distributional range of *C. tamala*. However, precaution should be used for accurate prediction of height outside the size and height ranges, site, and stand condition that differs from our study.

2. Materials and Methods

2.1. Study Area. The study was conducted at Mijure Danda Village Development Committee (VDC) of Kaski district, Nepal, which extends from 28°13'57" to 28°20'57"N latitude and 84°08'53" to 84°12'42"E longitude. The forest in the study area is managed by the Sikles unit of Annapurna Conservation Area Project (ACAP) and constitutes *C. tamala* as a dominant species having contiguous distribution pattern and with an Important Value Index (IVI) of 158.0 [27].

An IVI value was calculated by summing relative density, relative frequency, and relative dominance. The most frequent common associate species, with their IVI values, are *Schima wallichii* (77.89), *Castanopsis indica* (26.35), *Madhuca latifolia* (5.29), and *Macaranga postulata* (4.30) [27]. The study site falls under the humid subtropical monsoon climatic zone with hot and wet summers and relatively cold winters. The average monthly climate normal (1981-2010) temperature (minimum, maximum) to the nearest weather station was 21.1°C (13.4°C, 26.1°C) and precipitation was 325 mm (17.8 mm, 940.3 mm). Average annual precipitation was about 3900 mm year⁻¹ [47].

2.2. Data Collection and Processing. We collected the data through the inventory of natural stands of *C. tamala*, which includes 30 destructively sampled trees covering a wider range of H and D. Trees were selected for felling covering all the site conditions and tree size (H and D) distributions across the study sites in and outside of sampling plots. Nondestructive sample data came from a phytosociological survey of same forests [27]. We used systematic sampling plots with a size of 10 m × 10 m. Each plot has 5 m × 5 m subplots at northeast and southwest corners and 1 m × 1 m subplots at four corners. Information on species such as H and D were collected from 10 m × 10 m and 5 m × 5 m plots. The combined dataset size (n = 179) is smaller compared to other studies (e.g., [12, 13, 18, 48, 49]), but it can be used to construct H-D relationship models [50–52]. The combined dataset was split randomly into fitting (80%) and validation (20%) using R [53]. Summary statistics for H and D for both fitting and validation dataset are presented in Table 1.

2.3. Model Development and Evaluation. Initially, we selected 18 candidate nonlinear H-D relationship models (11 biparametric, and seven triparametric) based on a literature review (Table SA) to fit the model. We assumed that the total tree height is a function of diameter. In the later stage, we included only the models with all significant parameter estimates at 5% level of significance for further evaluation to compare their performance (Table 2). These models take the following functional form:

$$H_i = 1.3 + f(D_i, \mathbf{b}) + \varepsilon_i \quad (1)$$

where H_i is the i^{th} observation of the dependent variable tree height (m), D_i is the i^{th} observation of the independent variable diameter at breast height (cm), \mathbf{b} is the vector of parameter to be estimated, ε_i is the random error term, $f(\cdot)$ is a nonlinear function, and i is the i^{th} observation with $i = 1, 2, 3, \dots, n$. A constant term 1.3 is the height of stem above ground at which D was measured. We added this term in the function to avoid prediction of zero H when D approaches zero.

The nonlinear function “nls2”, an improved version of the function nls, in statistical software R [54, 55] was used to estimate model parameters using the ordinary least square method. There are several criteria to assess model performance [56]. We evaluated model performance based on

TABLE 1: Descriptive statistics of the variables for both fitting and validation dataset.

Statistic	Fitting (n = 143)		Validation (n = 36)	
	Diameter (cm)	Height (m)	Diameter (cm)	Height (m)
Minimum	1.00	2.10	2.00	2.40
Mean	13.26	8.07	11.14	7.09
Maximum	32.00	14.20	30.00	13.58
Standard Deviation	7.72	3.26	7.47	3.15

TABLE 2: Models selected for further evaluation, their designation, and parameters of the models.

Model	Designation	Parameter	Reference
$H_i = 1.3 + b_0 D^{b_1} + \varepsilon_i$	M1	2	[7]
$H_i = 1.3 + b_0 \left[1 - \exp(-b_1 D^{b_2}) \right] + \varepsilon_i$	M2	3	[33]
$H_i = 1.3 + b_0 \left[1 - \exp(-b_1 D) \right]^{b_2} + \varepsilon_i$	M3	3	[36]
$H_i = 1.3 + \frac{D}{(b_0 + b_1 D)} + \varepsilon_i$	M4	2	[37]
$H_i = 1.3 + \exp(b_0 D^{b_1}) + \varepsilon_i$	M5	2	[38]
$H_i = 1.3 + b_0 \exp\left(\frac{-b_1}{D}\right) + \varepsilon_i$	M6	2	[39]
$H_i = 1.3 + \left[\frac{D}{(1 + b_0 D)} \right]^{b_1} + \varepsilon_i$	M7	2	[1, 2]
$H_i = 1.3 + \frac{b_0 D}{(1 + D) + (b_1 D)} + \varepsilon_i$	M8	2	[40]
$H_i = 1.3 + \left[\frac{D}{(b_0 + b_1 D)} \right]^3 + \varepsilon_i$	M9	2	[41] cited in [13]
$H_i = 1.3 + \frac{b_0}{(1 + 1/(b_1 D^{b_2}))} + \varepsilon_i$	M10	3	[42]
$H_i = 1.3 + \frac{D^2}{(b_0 + b_1 D)^2} + \varepsilon_i$	M11	2	[43]
$H_i = 1.3 + \frac{b_0 D}{(b_1 + D)} + \varepsilon_i$	M12	2	[40, 44]
$H_i = 1.3 + \frac{b_0}{1 + b_1 \exp(D^{b_2})} + \varepsilon_i$	M13	3	[45]
$H_i = 1.3 + b_0 \exp(-b_1 \times \exp^{-b_2 D}) + \varepsilon_i$	M14	3	[46]
$H_i = 1.3 + b_0 \exp(-b_1 \times D^2) + \varepsilon_i$	M15	2	[2]

H_i is total height (m) of tree $i = 1, 2, 3, \dots, n$, D -diameter at breast height (cm), b_0 , b_1 , and b_2 are parameters to be estimated, 1.3 is added to avoid prediction of zero height when D approaches zero, and ε_i is a random error term which is assumed to be normally and identically distributed with mean 0 and variance σ^2 [NID $(0, \sigma^2)$].

numeric analysis of the following: (1) asymptotic t-statistics of parameters, (2) Root Mean Square Error (RMSE: see (2)), also known as a measure of model's precision, (3) mean bias (see (3)), and Mean Absolute Error (MAE: see (4)), and (4) information criteria—Akaike Information Criteria (AIC: see (5)) [56, 57] and Bayesian Information Criteria [58] (BIC: see (6)), followed by graphical presentation such as histogram, probability plots of residuals, and observed versus model predicted values. Criteria RMSE, AIC, BIC, Mean bias, and MAE are collectively called performance criteria. A coefficient of determination is not advisable to employ for assessing nonlinear regression. A statistic analogous to the coefficient of determination also called a fit index or modeling efficiency [14, 59] could be used. However, in this study, we did not use the fit index to evaluate our models as a fit index also suffers all the weaknesses of the coefficient of

determination [14].

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

$$\text{Mean bias} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{n} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n} \tag{4}$$

$$AIC = n \times \ln\left(\frac{RSS}{n}\right) + 2k \tag{5}$$

$$BIC = n \times \ln\left(\frac{RSS}{n}\right) + \ln(n) \times k \tag{6}$$

where y_i , \hat{y}_i are the observed and predicted values of height, respectively; n is the total number of observations used in model fitting; \ln is natural logarithm; RSS is the residual sums of squares; and k is the number of parameters in the model.

Models with least RMSE, AIC, BIC, mean bias, and MAE are considered to perform the best [60]. Reliability and validity of the model increase with its performance outside the test data [61–63]. However, due to limitation of dataset, model validation with an independent dataset covering more extensive geographical regions and management condition across the distributional ranges of species can be a potential topic for future research.

We evaluated models based on the significance of model parameters, performance criteria, and practical application. After initial performance screening, models were subjected to further comparison by ranking the performance criteria and considering the practical application of the model. The models with the least value of performance criteria (RMSE, AIC, BIC, mean bias, and MAE) received the highest ranking and vice versa. The rank value of each criterion was added to get the total sum of ranking, which was then ranked in ascending order—the lower the value, the better the model. The model with the smallest rank value was considered the best H-D relationship model of *C. tamala* naturally grown in mid-hill of Nepal.

3. Results

3.1. Descriptive Statistics and Parameter Estimates. Model parameters were estimated using nonlinear least squares techniques for the model fitting dataset. Descriptive statistics includes mean \pm st.dev (minimum, maximum) for both diameter and height [D (cm): 13.26 ± 7.72 (1.0, 32.0) and H (m): 8.07 ± 3.26 (2.1, 14.2)] for fitting dataset; and [D (cm): 11.14 ± 7.47 (2, 30) and H (m): 8.07 ± 3.15 (2.4, 13.58) for validation dataset]. All models were evaluated against multiple model performance criteria. Almost all (15) models (Table 3) showed significant parameter estimates ($p < 0.05$, unless otherwise mentioned) and were considered for further evaluation.

3.2. Model Performance and Selection. Parameter estimates of models indicate that the best model cannot be determined solely based on significant t-statistics. We additionally considered performance criteria values to assess the model's performance. Table 4 presents the parameter estimates and fit statistics associated with the selected models for fitting and validation dataset.

Among 15 models, M14 produced the least bias (0.012 m), followed by M1 (0.016 m). The values of RMSE ranged from 1.742 m (M14) to 2.42 m (M15). M14 yielded the least MAE (1.342 m) and AIC (568.541), while M15 produced the highest AIC (661.457) and BIC (670.346). M14 performed significantly better than other models, produced similar parameter estimates for validation dataset (Table 6), and similar fit statistics for fitting and validation dataset (Table 4).

We ranked models based on values of performance criteria and calculated average rank on sum ranks of performance criteria. M14 performed the best (rank = 1) for

the fitting dataset, while M14, M12, and M4 performed the best with equal rank (rank = 1) for the validation dataset (Table 5). Although M14, M12, and M4 have identical rank for validation dataset, we considered M14 the best model because it performed the best (rank = 1) for fitting dataset too, while M4 and M12 were the third best models for fitting dataset. Parameter estimates of M4 and M12 for validation dataset (Table SB), graph of the model, and residual distribution (Figures SA and SB) confirm that the models M4 and M12 are the best alternatives to model M14. Interestingly, M12 an M4 yielded strikingly similar performance statistics (identical to the three-decimal place) for model fitting, validation, and combined dataset (Tables 4 and SB).

3.3. Residual Analysis and Shapiro-Wilk Test. To come up with the best model, we used test for residual normality. Residuals graphs (histograms, probability plots) and plot of fitted line overlaid on the observed heights data were produced for a visual check. Figure 1 presents the plot of residuals against the observed diameters of fitting data. Most of the models showed no systematic departure from random pattern.

The Shapiro-Wilk test of residuals of the best three models [M14- ($W = 0.990$, $p = 0.4143$) for fitting and ($W = 0.978$, $p = 0.6858$) for validation; M12- ($W = 0.984$, $p = 0.627$) for fitting and ($W = 0.984$, $p = 0.871$) for validation; M4- ($W = 0.984$, $p = 0.627$) for fitting and ($W = 0.984$, $p = 0.871$)] showed a p value greater than 0.05, which suggests that residuals do not violate the assumption of normal random error. Figure 2 shows curves of the best fitting model M14 for fitting and validation dataset and histogram of residuals with a superimposed normal curve. Normally, the model tended to overestimate for shorter trees with larger diameter size.

3.4. Paired t-Tests. The paired t-test of M14 with observed height values revealed insignificant statistics [$t(142) = 0.084$, $p = 0.933$]. Similarly, the paired t-test of observed height values with predicted heights of M12 [$t(142) = 0.1734$, $p = 0.8625$] and M4 [$t(142) = 0.1368$, $p = 0.8914$] for fitting dataset also resulted in statistically insignificant statistics. To determine the better model between M12 and M4, we compared the predicted height from both models between them and with the predicted height from the best model, i.e., M14. Our results of paired t-test to compare the predicted heights showed significant statistics between M4 and M12 [$t(142) = 3.1143$, $p = 0.002$] and between M12 and M14 [$t(142) = -2.8968$, $p = 0.0044$]. The M4 showed no significant difference in mean predicted heights from the M14 [$t(142) = -0.8743$, $p = 0.3983$]. This suggests that the M14 has more accurate prediction power followed by M4.

4. Discussion

Almost all the candidate models performed well in explaining H-D relationship for *C. tamala* trees grown under natural forest. Model selection based on multiple criteria suggested that M14, M12, and M4 were more effective in predicting *C. tamala* tree height compared to other candidate models.

TABLE 3: Parameter estimates of the selected models.

Model	Parameter	Coefficient	Std. error	t	p-value
M1	b0	1.3491	0.1629	8.2812	<0.001
	b1	0.6413	0.042	15.262	<0.001
M2	b0	13.7193	2.3975	5.7223	<0.001
	b1	0.0544	0.0109	5.0132	<0.001
	b2	1.0229	0.1495	6.84	<0.001
M3	b0	14.1312	2.3256	6.0765	<0.001
	b1	0.0546	0.0242	2.2579	0.0255
	b2	0.9905	0.1974	5.0186	<0.001
M4	b0	1.201	0.1003	11.9712	<0.001
	b1	0.0467	0.0057	8.2513	<0.001
M5	b0	0.8545	0.0583	14.6447	<0.001
	b1	0.3158	0.0228	13.844	<0.001
M6	b0	13.9604	0.6916	20.1857	<0.001
	b1	7.9528	0.6879	11.5609	<0.001
M7	b0	14.3409	0.716	20.0279	<0.001
	b1	8.6811	0.7223	12.0191	<0.001
M8	b0	0.8326	0.0696	11.9712	<0.001
	b1	-0.9611	0.0078	-123.26	<0.001
M9	b0	1.4599	0.123	11.8697	<0.001
	b1	0.4002	0.0081	49.4891	<0.001
M10	b0	20.4373	6.8756	2.9724	0.0035
	b1	0.0388	0.0075	5.1557	<0.001
	b2	1.0301	0.2058	5.0051	<0.001
M11	b0	1.6013	0.1337	11.9776	<0.001
	b1	0.2454	0.0084	29.0816	<0.001
M12	b0	21.4115	2.5949	8.2514	<0.001
	b2	25.715	5.1563	4.9871	<0.001
M13	b0	11.3241	0.498	22.7401	<0.001
	b1	6.3863	1.1227	5.6884	<0.001
	b2	0.0169	0.0019	8.9606	<0.001
M14	b0	12.1112	0.7606	15.9236	<0.001
	b1	2.3069	0.2262	10.1997	<0.001
	b2	0.115	0.0163	7.0766	<0.001
M15	b0	5.2026	0.2344	22.1983	<0.001
	b1	-0.001	0.0001	-11.628	<0.001

The Gompertz model (M14) demonstrated competitive performance statistics for both fitting and validation dataset. Although Gompertz model follows growth theory ([8], Nord-Larsen and Cao 2006; Schmidt et al. 2011), it generally underestimates tree heights [10, 52]. Several studies have used the Gompertz model to describe the height-diameter relationship (Rupšys et al. 2011; Özçelik et al. 2013; [52, 64]). Zhang (1997) selected six models for evaluating H-D relationship and found that the Gompertz model underestimates tree heights for larger sizes trees ($D > 100$ cm). Similarly, in our case, the Gompertz model tended to underestimate heights (10.84%) for taller trees with a larger diameter ($H \geq 12$ m and $D \geq 17$ cm). *C. tamala* trees from dominant crown category grow taller, larger, and faster. Trees under shade allocate more biomass to diameter growth than height as height growth requires more competitive advantage [65, 66]. This indicates

that *C. tamala* H-D relationship at our study site might have been mediated by shade tolerance or crown dominance. Studies have shown that shade tolerance and climate jointly effect on allometric variation [66–68]. However, assessing the possible variation in *C. tamala* H-D relationship is beyond the scope of this study due to the small size of our dataset.

H-D relationship models are often developed based on sampling data from permanent sample plots that are monitored for a relatively extended period [59, 64, 69, 70]. Studies that employed longitudinal data along with other plot-level covariates in nonlinear mixed H-D relationship models show improved model performance compared to ordinary nonlinear least square models [18, 52, 59, 71, 72]. Although the inclusion of stand variables may improve the prediction power of the model, this often requires greater sampling efforts especially when data collection involves an

TABLE 4: Performance statistics of selected models for fitting and validation dataset.

Model	Performance Criteria							
	Fitting					Validation		
	Bias (m)	RMSE (m)	MAE	AIC	BIC	Bias (m)	RMSE (m)	MAE
M1	-0.016	1.801	1.381	576.972	585.861	-0.206	1.481	1.133
M2	0.033	1.777	1.382	574.167	586.019	-0.078	1.573	1.195
M3	0.025	1.777	1.381	574.185	586.036	-0.094	1.565	1.188
M4	0.020	1.776	1.381	573.093	581.981	-0.109	1.530	1.179
M5	-0.073	1.863	1.430	586.684	595.573	-0.341	1.523	1.195
M6	0.163	1.896	1.521	591.819	600.708	0.157	1.848	1.441
M7	0.136	1.869	1.494	587.717	596.606	0.112	1.794	1.393
M8	0.012	1.796	1.380	574.093	582.981	-0.129	1.639	1.179
M9	0.115	1.827	1.452	581.215	590.104	0.075	1.703	1.322
M10	0.025	1.782	1.383	575.072	586.923	-0.098	1.560	1.185
M11	0.090	1.804	1.427	577.579	586.467	0.029	1.644	1.277
M12	0.020	1.776	1.381	573.093	581.981	-0.109	1.530	1.179
M13	0.018	1.752	1.352	569.226	580.077	-0.190	1.546	1.138
M14	0.012	1.742	1.342	568.541	580.392	-0.106	1.546	1.149
M15	-0.050	2.419	1.972	661.457	670.346	-0.606	2.176	1.743

TABLE 5: Rank of selected models based on performance criteria for fitting and validation dataset.

Model	Performance Criteria									
	Fitting Rank						Validation Rank			
	Bias	RMSE	MAE	AIC	BIC	Sum (Rank)	Bias	RMSE	MAE	Sum (Rank)
M1	3	9	4	9	6	31(6)	13	1	1	15(4)
M2	9	5	8	6	7	35(8)	3	9	9	21(8)
M3	7	5	4	7	8	31(6)	4	8	8	20(7)
M4	5	3	4	3	3	18(3)	7	3	4	14(1)
M5	11	12	11	12	12	58(11)	14	2	9	25(11)
M6	15	14	14	14	14	71(15)	11	14	14	39(14)
M7	14	13	13	13	13	66(13)	9	13	13	35(13)
M8	1	8	3	5	5	22(5)	10	10	4	24(10)
M9	13	11	12	11	11	58(11)	2	12	12	26(12)
M10	7	7	9	8	10	41(9)	5	7	7	19(5)
M11	12	10	10	10	9	51(10)	1	11	11	23(9)
M12	5	3	4	3	3	18(3)	7	3	4	14(1)
M13	4	2	2	2	1	11(2)	12	5	2	19(5)
M14	1	1	1	1	2	6(1)	6	5	3	14(1)
M15	10	15	15	15	15	70(14)	15	15	15	45(15)

invasive sampling approach. Our study did not include such covariates because of the cross-sectional nature of data that were collected from both inside and outside of sample plots. Future researchers can test the validity of our model and improve the predictive performance utilizing stand and plot-level covariates when available.

Predictive performance of the models beyond the observed range was not possible as the fitting dataset has larger sizes and taller trees. Independent datasets from different geographical locations and management systems with larger and taller trees than those used in this study

could confirm the predictive power of the model [14]. Motallebi and Kangur [73], using the annual height and diameter increment data of 114 trees (observation periods spanned from 40 to 115 years) from three European countries, indicated a variable allometric relationship (significant coefficients across sites) between tree height and diameter which did not follow elasticity or geometric scaling rules across sites. H-D relationship varies among ecoregions due to differences in bioclimatic conditions [48, 69, 74] and among management regimes [32]. Therefore, H-D relationship of species should be evaluated across climatic and management

TABLE 6: Prediction statistics of the best model (M14) for validation dataset.

Dataset	Parameter	Coefficient	Std. error	t	p-value	RMSE	Mean Bias
Validation Data	b_0	17.63702	5.484934	3.21554	0.00291	1.439	0.0008
$n = 36$	b_1	2.266303	0.218373	10.3781	<0.0001		
	b_2	0.063602	0.023551	2.70063	0.01084		

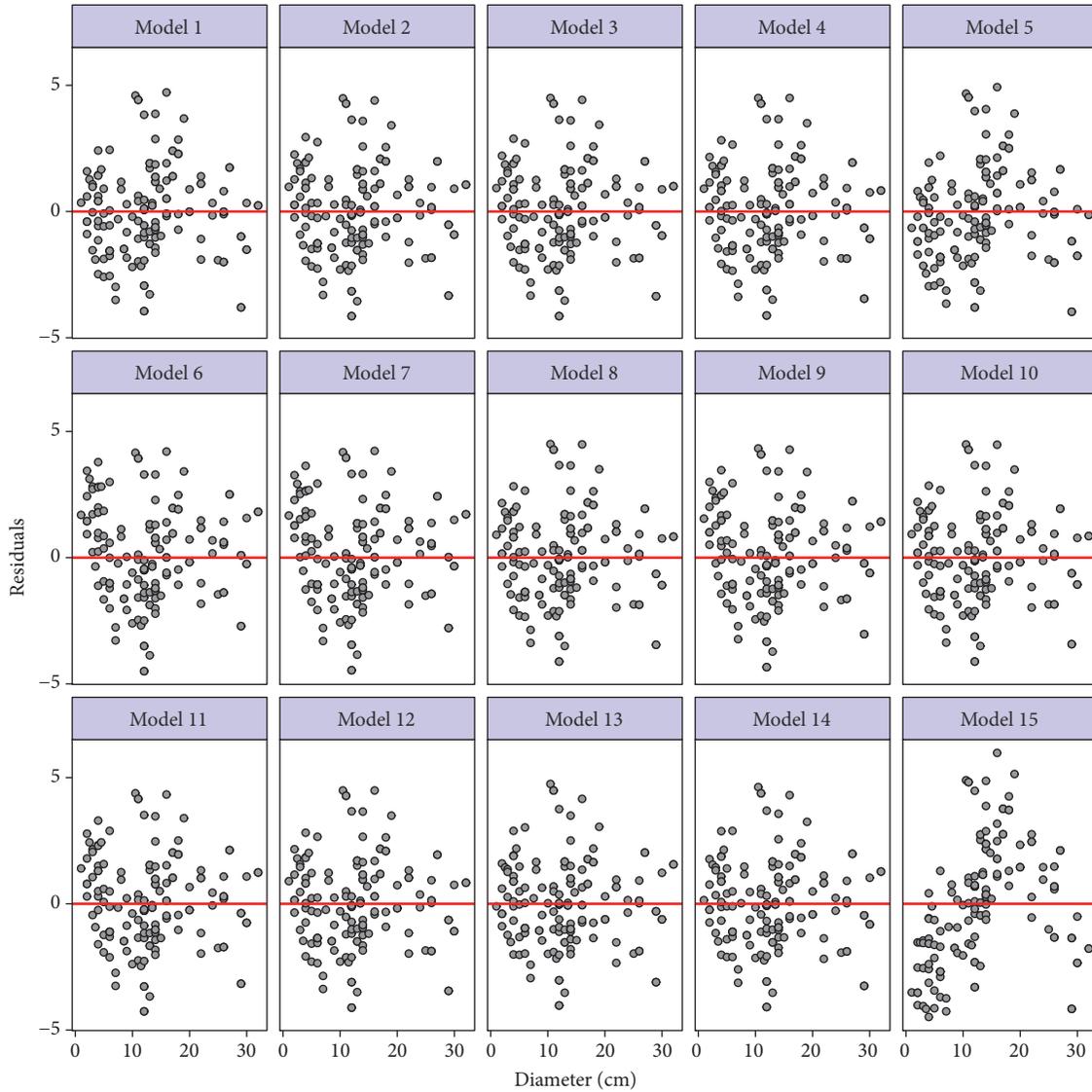


FIGURE 1: Residuals analysis plots of 15 H-D relationship models fitted for *Cinnamomum tamala*.

systems to understand the changes in the stem allometry of species. As *C. tamala* prefers moisture rich areas, water stress could change the H-D relationship. Therefore, the inclusion of water availability in original H-D relationship models and a mixed-effect modeling approach could further optimize the model's performance. Since this study's fitting and validation data came from same climatic and management conditions, validation of these models with independent data from different geographic, climatic, and management practices could be a potential topic for future research.

5. Conclusion

We calibrated and tested 18 nonlinear models on *Cinnamomum tamala* trees grown under the natural multilayer tree structure in mid-hills of Nepal. The best model was selected based on multiple performance criteria, error diagnostics, growth theory, and practical application. Results showed that the Gompertz model (M14) best fitted the fitting dataset and performed consistently on the validation dataset and can be used reliably in biomass estimation and management for *C. tamala* trees in the mid-hills of Nepal.

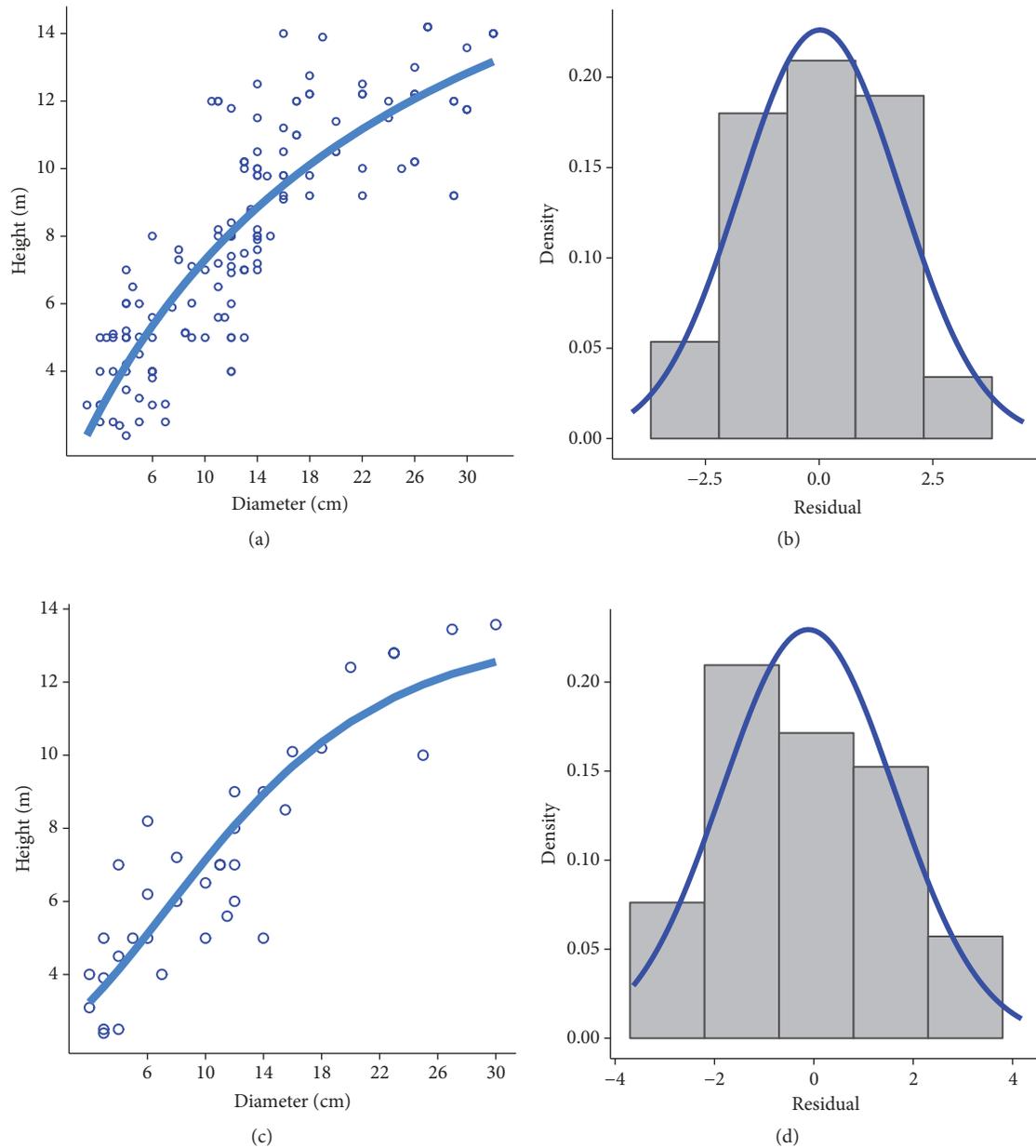


FIGURE 2: Scatter plot of total height (H) against D superimposed with M14 for fitting data (a) and validation data (c); a histogram of residuals of M14 for fitting data (b) and validation dataset (d).

The existing studies on *C. tamala* height-diameter (H-D) modeling are limited to even-aged stands or plantation and have not attempted to develop H-D relationship models under natural forests. The methodology presented in this paper utilizes ordinary nonlinear models to generate H-D relationship in the uneven-aged natural forest of *C. tamala*. Since we considered diameter as the only predictor variable, caution should be applied while using our model to other forests stands that differ in site and stand conditions to the basis of this study. In future research, our model can be extended to other regions and management regimes (e.g., the tree outside forestry), following updates through refitting and validation against independent data from the broadest

possible ranges of size, site, and stand conditions, including stand and plot attributes across the distributional ranges of *C. tamala*.

Data Availability

The data used in this paper came from phytosociological survey of *Cinnamomum tamala* forests (natural). Of the total trees used in the analysis, 30 trees were sampled destructively which was previously used in bark biomass production model. If required, raw dataset can be made available. R-code used in the analysis is presented at the end of the Supplementary Materials.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

We want to thank The National Trust for Nature Conservation/Annapurna Conservation Area Project (NTNC/ACAP), for providing financial support to this study. This work was also supported by the United State Department of Agriculture (USDA), National Institute of Food and Agriculture (NIFA), McIntire Stennis Project # 1017946. We extend our thanks to Conservation Area Management Committee members of Mijure danda Village Development Committee. Thanks are due to people who rendered assistance during field works, especially, Bishwa Kiran Giri, Hari Prasad Subedi, and Rishi Ranabhat.

Supplementary Materials

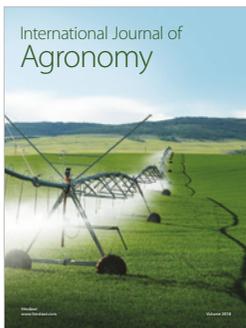
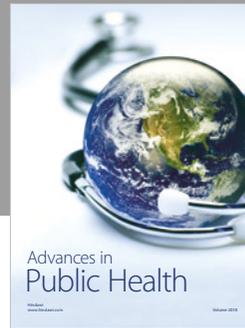
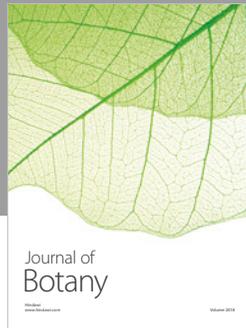
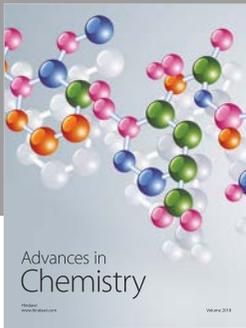
Table SA: selected 18 models. Table SB: parameter estimates and fit statistics of M4 and M12. Figure SA: fitted model and histogram for validation dataset of M4 and M12. Figure SB: fitted model and histogram for combined dataset of M4 and M12. R-Code used in the analysis. (*Supplementary Materials*)

References

- [1] R. O. Curtis, "Height-diameter and height-diameter-age equations for second-growth douglas-fir," *Forest Science*, vol. 13, pp. 365–375, 1967.
- [2] S. Huang, D. Price, and S. J. Titus, "Development of ecoregion-based height-diameter models for white spruce in boreal forests," *Forest Ecology and Management*, vol. 129, no. 1-3, pp. 125–141, 2000.
- [3] J. Chave, C. Andalo, S. Brown et al., "Tree allometry and improved estimation of carbon stocks and balance in tropical forests," *Oecologia*, vol. 145, no. 1, pp. 87–99, 2005.
- [4] P. Saud, T. B. Lynch, and J. M. Guldin, "Twenty five years long survival analysis of an individual shortleaf pine trees," in *Proceedings of the 18th biennial southern silvicultural research conference*, J. S. Callie, K. C. Wayne, and C. M. Oswalt, Eds., pp. 555–557, 2016.
- [5] K. C. Colbert, D. R. Larsen, and J. R. Lootens, "Height-diameter equations for thirteen midwestern bottomland hardwood species," *Northern Journal of Applied Forestry*, vol. 19, no. 4, pp. 171–176, 2002.
- [6] Y.-F. Wang, T.-X. Yue, Z.-P. Du, and M.-W. Zhao, "Improving the accuracy of the height-diameter equation using the classified factors method," *Environmental Earth Sciences*, vol. 74, no. 8, pp. 6471–6480, 2015.
- [7] J. S. Huxley and G. Teissier, "Terminology of relative growth," *Nature*, vol. 137, pp. 780–781, 1936.
- [8] K. Eerikäinen, "Predicting the height-diameter pattern of planted Pinus kesiya stands in Zambia and Zimbabwe," *Forest Ecology and Management*, vol. 175, no. 1-3, pp. 355–366, 2003.
- [9] R. Calama and G. Montero, "Interregional nonlinear height-diameter model with random coefficients for stone pine in Spain," *Canadian Journal of Forest Research*, vol. 34, no. 1, pp. 150–163, 2004.
- [10] J. Castaño-Santamaría, F. Crecente-Campo, J. L. Fernández-Martínez, M. Barrio-Anta, and J. R. Obeso, "Tree height prediction approaches for uneven-aged beech forests in northwestern Spain," *Forest Ecology and Management*, vol. 307, pp. 63–73, 2013.
- [11] P. Rupšys, "Height-diameter models with stochastic differential equations and mixed-effects parameters," *Journal of Forest Research*, vol. 20, pp. 9–17, 2014.
- [12] T. Aishan, Ü. Halik, F. Betz, P. Gärtner, and B. Cyffka, "Modeling height-diameter relationship for Populus euphratica in the Tarim riparian forest ecosystem, Northwest China," *Journal of Forestry Research*, vol. 27, no. 4, pp. 889–900, 2016.
- [13] R. P. Sharma, Z. Vacek, and S. Vacek, "Nonlinear mixed effect height-diameter model for mixed species forests in the central part of the Czech Republic," *Journal of Forest Science (JFS)*, vol. 62, no. 10, pp. 470–484, 2016.
- [14] J. K. Vanclay, *Modelling Forest Growth and Yield: Applications to Mixed Tropical Forests*, CAB International Wallingford, 1994.
- [15] L. Poorter, F. Bongers, F. J. Sterck, and H. Wöll, "Architecture of 53 rain forest tree species differing in adult stature and shade tolerance," *Ecology*, vol. 84, no. 3, pp. 602–608, 2003.
- [16] M. Sharma and J. Parton, "Height-diameter equations for boreal tree species in Ontario using a mixed-effects modeling approach," *Forest Ecology and Management*, vol. 249, no. 3, pp. 187–198, 2007.
- [17] D. I. Forrester, A. Benneter, O. Bouriaud, and J. Bauhus, "Diversity and competition influence tree allometric relationships – developing functions for mixed-species forests," *Journal of Ecology*, vol. 105, no. 3, pp. 761–774, 2017.
- [18] L. Mehtätalo, S. de-Miguel, and T. G. Gregoire, "Modeling height-diameter curves for prediction," *Canadian Journal of Forest Research*, vol. 45, no. 7, pp. 826–837, 2015.
- [19] D. M. Edwards, "The trade in non-timber forest products from Nepal," *Mountain Research and Development*, vol. 16, no. 4, pp. 383–394, 1996.
- [20] B. Ghosh, "Regeneration ecology and sustainability of harvest of bay leaf, Cinnamomum tamala R Nees (lauraceae) in Meghalaya, Shillong," 2007.
- [21] G. Sharma, B. P. Nautiyal, and A. R. Nautiyal, "Seedling emergence and survival in Cinnamomum tamala under varying micro-habitat conditions: Conservation implications," *Tropical Ecology*, vol. 50, no. 1, pp. 201–209, 2009.
- [22] G. Sharma and A. R. Nautiyal, "Cinnamomum tamala: a valuable tree from Himalayas," *International Journal of Medicinal and Aromatic Plants*, vol. 1, pp. 12–15, 2011.
- [23] J. Jackson, *Manual of afforestation in Nepal*, Forest Research and Survey Centre, Kathmandu, Nepal, 2nd edition, 1994.
- [24] DOF, Hamro Ban, Extension Division, Kathmandu, Nepal, 2010.
- [25] D. Lamichhane and N. K. Karna, "Harvesting methods of Cinnamomum tamala leaves in private land: a case study from Udayapur district, Nepal," *Banko Janakari*, vol. 19, no. 2, pp. 20–24, 2009.
- [26] R. S. Chauhan, D. Tiwari, A. Bisht, and A. Shukla, "Ex situ conservation of medicinal and aromatic plants in Bharsar, Uttarakhand, India," *Medicinal Plants*, vol. 6, pp. 282–292, 2014.
- [27] M. R. Subedi and Y. P. Timilsina, "Distribution pattern of cinnamomum tamala in annapurna conservation area, Kaski, Nepal," *Nepal Journal of Science and Technology*, vol. 15, pp. 29–36, 2015.
- [28] P. C. Phondani, I. D. Bhatt, V. S. Negi, B. P. Kothyari, A. Bhatt, and R. K. Maikhuri, "Promoting medicinal plants cultivation

- as a tool for biodiversity conservation and livelihood enhancement in Indian Himalaya,” *Journal of Asia-Pacific Biodiversity*, vol. 9, no. 1, pp. 39–46, 2016.
- [29] V. S. Negi, P. Kewlani, R. Pathak et al., “Criteria and indicators for promoting cultivation and conservation of Medicinal and Aromatic Plants in Western Himalaya, India,” *Ecological Indicators*, vol. 93, pp. 434–446, 2018.
- [30] TISC, Biomass Table of Tejpat, 2003.
- [31] B. S. Poudel, S. K. Gautam, and D. N. Bhandari, “Above-ground tree biomass and allometric relationships of *Cinnamomum tamala* grown in the western hill regions of Nepal,” *Banko Janakari*, vol. 21, pp. 3–12, 2011.
- [32] M. R. Subedi and R. P. Sharma, “Allometric biomass models for bark of *Cinnamomum tamala* in mid-hill of Nepal,” *Biomass & Bioenergy*, vol. 47, pp. 44–49, 2012.
- [33] B. Zeide, “Analysis of Growth Equations,” *Forest Science*, vol. 39, no. 3, pp. 594–616, 1993.
- [34] M. S. Watt and M. U. F. Kirschbaum, “Moving beyond simple linear allometric relationships between tree height and diameter,” *Ecological Modelling*, vol. 222, no. 23–24, pp. 3910–3916, 2011.
- [35] C. E. T. Paine, T. R. Marthews, D. R. Vogt et al., “How to fit nonlinear plant growth models and calculate growth rates: An update for ecologists,” *Methods in Ecology and Evolution*, vol. 3, no. 2, pp. 245–256, 2012.
- [36] F. J. Richards, “A flexible growth function for empirical use,” *Journal of Experimental Botany*, vol. 10, no. 2, pp. 290–301, 1959.
- [37] K. Hosoda and T. Iehara, “Aboveground biomass equations for individual trees of *Cryptomeria japonica*, *Chamaecyparis obtusa* and *Larix kaempferi* in Japan,” *Journal of Forest Research*, vol. 15, no. 5, pp. 299–306, 2010.
- [38] R. P. Sharma, “Allometric models for total-tree and component-tree biomass of *Alnus nepalensis* D. Don in Nepal,” *Indian Forester*, vol. 137, pp. 1386–1390, 2011.
- [39] F. X. Schumacher, “A new growth curve and its application to timber yield studies,” *Journal of Forestry*, vol. 37, pp. 819–820, 1939.
- [40] B. C. Larson, “Development and growth of even-aged stands of Douglas-fir and grand fir,” *Canadian Journal of Forest Research*, vol. 16, no. 2, pp. 367–372, 1986.
- [41] M. Näslund, “Skogsforsö ksstaltens gallringsforsök i tallskog,” *Meddelanden från Statens Skogsförsöksanstalt*, vol. 29, pp. 1–169, 1936.
- [42] D. A. Ratkowsky and D. E. A. Giles, *Handbook of Nonlinear Regression Models*, M. Dekker, New York, NY, USA, 1990.
- [43] F. Loetsch, F. Zöhrer, and K. E. Haller, *Forest Inventory*, BLV Verlagsgesellschaft, Munich, 1973.
- [44] D. A. Ratkowsky and T. J. Reedy, “Choosing near-linear parameters in the four-parameter logistic model for radioligand and related assays,” *Biometrics*, vol. 42, no. 3, pp. 575–582, 1986.
- [45] R. Pearl and L. J. Reed, “On the rate of growth of the population of the United States since 1790 and its mathematical representation,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 6, p. 275, 1920.
- [46] C. P. Winsor, “The Gompertz curve as a growth curve,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 18, no. 1, pp. 1–8, 1932.
- [47] DHM, Climate normals. Kathmandu, Nepal, 2010.
- [48] S. Corral-Rivas, J. Álvarez-González, F. Crecente-Campo, and J. Corral-Rivas, “Local and generalized height-diameter models with random parameters for mixed, uneven-aged forests in Northwestern Durango, Mexico,” *Forest Ecosystems*, vol. 1, no. 6, 2014.
- [49] Y. Q. Li, X. W. Deng, Z. H. Huang et al., “Development and evaluation of models for the relationship between tree height and diameter at breast height for Chinese-fir plantations in subtropical China,” *PLoS ONE*, vol. 10, pp. 1–21, 2015.
- [50] E. L. M. H. Osman, E. L. Z. A. Idris, and E. L. M. M. Ibrahim, “Modelling height-diameter relationships of selected economically important natural forests species,” *Journal of forest products and industries*, vol. 2, pp. 34–42, 2013.
- [51] R. A. F. De Lima, J. L. F. Batista, and P. I. Prado, “Modeling tree diameter distributions in natural forests: An evaluation of 10 statistical models,” *Forest Science*, vol. 61, no. 2, pp. 320–327, 2015.
- [52] T. Misik, K. Antal, I. Kárász, and B. Tóthmérész, “Nonlinear height-diameter models for three woody, understory species in a temperate oak forest in Hungary,” *Canadian Journal of Forest Research*, 2016.
- [53] R Core Team, *R: A Language and Environment for Statistical Computing*, 2017.
- [54] G. Grothendieck, “nls2: Non-linear regression with brute force,” 2013.
- [55] R Core Team, *A language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna, Austria, 2018.
- [56] K. P. Burnham and D. R. Anderson, *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*, Springer, New York, NY, USA, 2nd edition, 2002.
- [57] H. Akaike, “A new look at the statistical model identification,” *IEEE Transactions on Automatic Control*, vol. 19, pp. 716–723, 1974.
- [58] G. Schwarz, “Estimating the dimension of a model,” *The Annals of Statistics*, vol. 6, no. 2, pp. 461–464, 1978.
- [59] P. Saud, T. B. Lynch, K. C. Anup, and J. M. Guldin, “Using quadratic mean diameter and relative spacing index to enhance height–diameter and crown ratio models fitted to longitudinal data,” *Forestry: An International Journal of Forest Research*, vol. 89, no. 2, pp. 215–229, 2016.
- [60] J. K. Vanclay, “Evaluating forest growth models,” *Ecological Modelling*, vol. 98, pp. 1–12, 1997.
- [61] M. Stone, “Cross-validated choice and assessment of statistical predictions,” *Journal of the Royal Statistical Society*, vol. 36, pp. 111–147, 1974.
- [62] R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” in *Proceedings of the 14th International Conference on AI (IJCAI)*, pp. 1137–1145, 1995.
- [63] S. Arlot and A. Celisse, “A survey of cross-validation procedures for model selection,” *Statistics Surveys*, vol. 4, pp. 40–79, 2010.
- [64] A. Cuni-Sanchez, M. Pfeifer, R. Marchant et al., “New insights on above ground biomass and forest attributes in tropical montane forests,” *Forest Ecology and Management*, vol. 399, pp. 235–246, 2017.
- [65] S. Bohlman and S. O’Brien, “Allometry, adult stature and regeneration requirement of 65 tree species on Barro Colorado Island, Panama,” *Journal of Tropical Ecology*, vol. 22, no. 2, pp. 123–136, 2006.
- [66] D. A. King, S. J. Davies, and N. S. M. Noor, “Growth and mortality are related to adult tree size in a Malaysian mixed dipterocarp forest,” *Forest Ecology and Management*, vol. 223, no. 1–3, pp. 152–158, 2006.

- [67] A. Sumida, T. Miyaura, and H. Torii, "Relationships of tree height and diameter at breast height revisited: Analyses of stem growth using 20-year data of an even-aged *Chamaecyparis obtusa* stand," *Tree Physiology*, vol. 33, no. 1, pp. 106–118, 2013.
- [68] T. Franceschini and R. Schneider, "Influence of shade tolerance and development stage on the allometry of ten temperate tree species," *Oecologia*, vol. 176, no. 3, pp. 739–749, 2014.
- [69] F. Crecente-Campo, M. Tomé, P. Soares, and U. Diéguez-Aranda, "A generalized nonlinear mixed-effects height-diameter model for *Eucalyptus globulus* L. in northwestern Spain," *Forest Ecology and Management*, vol. 259, no. 5, pp. 943–952, 2010.
- [70] P. O. Ige, G. O. Akinyemi, and A. S. Smith, "Nonlinear growth functions for modeling tree height-diameter relationships for *Gmelina arborea* (Roxb.) in south-west Nigeria," *Forest Science and Technology*, vol. 9, no. 1, pp. 20–24, 2013.
- [71] P. Adame, M. del Río, and I. Cañellas, "A mixed nonlinear height-diameter model for pyrenean oak (*Quercus pyrenaica* Willd.)," *Forest Ecology and Management*, vol. 256, no. 1-2, pp. 88–98, 2008.
- [72] H. Xu, Y. Sun, X. Wang et al., "Nonlinear mixed-effects (NLME) diameter growth models for individual China-fir (*Cunninghamia lanceolata*) trees in southeast China," *PLoS ONE*, vol. 9, pp. 1–10, 2014.
- [73] A. Motallebi and A. Kangur, "Are allometric relationships between tree height and diameter dependent on environmental conditions and management?" *Trees - Structure and Function*, vol. 30, no. 4, pp. 1429–1443, 2016.
- [74] S. X. Meng, S. Huang, V. J. Lieffers, T. Nunifu, and Y. Yang, "Wind speed and crown class influence the height-diameter relationship of lodgepole pine: Nonlinear mixed effects modeling," *Forest Ecology and Management*, vol. 256, no. 4, pp. 570–577, 2008.



Hindawi

Submit your manuscripts at
www.hindawi.com

