Modeling tree volume for *Terminalia Tomentosa* in Mixed Tropical Hardwood forest in Karnali Province, Nepal

A report submitted by

Sinjali Krishi Ban Private limited,

Jumla

Submitted to

Forest Research and Training Centre

Karnali province

Surkhet

Fiscal year : 2080/081

Modeling tree volume for *Terminalia Tomentosa* in Mixed Tropical Hardwood forest in Karnali Province, Nepal

Abstract

Terminalia tomentosa, an associate species of Shorea robusta, is a pivotal commercial tree in the lowlands of Nepal, holding significant socio-economic importance. Developing an allometric volume equation for this species is essential for accurately assessing current stock and forecasting future growth. This study developed a stem volume function for *T. tomentosa,* derived from 195 sampled trees across managed mixed hardwood forests in the lowland regions of Karnali Province, Nepal. Various mathematical models were evaluated using non-linear least square regression with diameter at breast height (DBH) and total tree height (H) as predictor variables. Among the growth functions evaluated (power, fractional, and exponential), the power function provided the best fit (R^2_adj = 0.97; RMSE = 0.14, AIC = -194.14), with no systematic residual trends observed. Model simulations indicated that tree volume increases with tree height. The presented model demonstrated statistical flexibility and biological plausibility, making it suitable for precise volume prediction of *T. tomentosa.* Prediction accuracy can be further enhanced, and the model's applicability broadened, by recalibrating it to include additional predictor variables (e.g., site and climate factors) and incorporating more data from diverse distributions of the species across the lowland regions of Karnali Province and beyond. Potential differences may arise with validation using independent data reflecting diverse site and stand attributes. The simplicity and robustness of the developed model are expected to enhance the management of *T. tomentosa* in mixed hardwood forests.

Keywords: **allometric volume equation, exponential function, power function, models, non-destructive sampling**

Introduction

In the intricate domain of forestry management, the accurate estimation of forest growing stock stands as a cornerstone, indispensable for crafting and implementing sustainable practices that balance ecological preservation with economic utilization (Aryal et al., 2023; Zianis & Mencuccini, 2004; Zianis et al., 2005). These estimations serve not only as vital inputs for decision support systems but also as crucial metrics for evaluating the health and productivity of forest ecosystems (Baral et al., 2021; Lucas et al., 2006).

Quantifying forest growing stock, often represented as stand volume, is integral to effective forest management practices. Traditionally, this assessment has relied on direct methods such as tree harvesting or fresh measurements on-site. However, the practicality of these approaches is often hindered by their high costs, labor intensiveness, and susceptibility to errors, particularly in the context of large forested areas or remote locations (Basuki et al., 2009).

In response to the challenges posed by traditional direct methods of estimating forest growing stock, the forestry community has increasingly embraced indirect methods, particularly the utilization of established volume models. These models establish correlations between easily measurable tree attributes such as diameter at breast height (DBH), tree height, and crown dimensions, and the overall stand volume. By leveraging these models, forest managers can derive estimations of growing stock that are not only cost-effective but also reliable, facilitating informed decision-making processes (Chaturvedi & Raghubanshi, 2012; Subedi & Sharma, 2012).

Volume models offer a practical alternative to direct methods, providing accurate estimates while minimizing resource expenditure (Aryal et al., 2023; Chaturvedi & Raghubanshi, 2012; Subedi & Sharma, 2012). These models are instrumental in assessing both the current stock and the future growth potential of forest stands, crucial considerations for sustainable forest management practices (Zianis et al., 2005).

Furthermore, precise estimations of growing stock are indispensable for maintaining ecological balance and ensuring effective carbon accounting within forest ecosystems (Lucas et al., 2006; Baral et al., 2018). While direct methods and forest inventories offer high precision, they often entail significant resource investment and time consumption. Conversely, models that establish correlations between volume and readily available tree attributes provide a more efficient and cost-effective means of estimating growing stock (Chaturvedi et al., 2012; Subedi & Sharma, 2012).

By employing such models, forest managers can optimize resource allocation, monitor ecosystem health, and make informed decisions regarding forest utilization and conservation efforts. Ultimately, the adoption of volume models represents a significant step towards achieving sustainable forest management practices, ensuring the long-term viability of forest ecosystems and the services they provide. These mathematical relationships, commonly expressed as allometric or volume equations, allow for the estimation of growing stock based on easily measurable tree attributes. By utilizing such models, forest managers can optimize resource allocation and make informed decisions regarding forest utilization and conservation efforts, thereby ensuring the long-term sustainability of forest ecosystems.

Estimating present and future stand volume and harvested volume often relies on volume equations(Özçelik et al., 2010). Most allometries employ diameter at breast height (DBH) as the only independent variable(Gower et al., 1999). Precision can be increased when tree height is included as a second predictor(Malata et al., 2017; Tewari & Singh, 2018; Thangjam et al., 2019). Recently, the effect of crown dimensions on the estimation of the stem volume and total tree biomass has been reported in various palnt species(Aryal et al., 2023; Ver Planck & MacFarlane, 2014; Baral et al., 2021). However, it has been suggested to use DBH as a single predictor variable, as it is easily obtained, has little error and is widely available in timber inventory (Özçelik, 2008; Wagle & Sharma, 2011; Wang et al., 2015). Even though volume equations have been studied for many years, new models are still being published as the volume-DBH relationship varies by species (Muhairwe, 1999). Moreover, species respond differently to their growing environment and management decisions(Pérez, 2003; Skovsgaard & Vanclay, 2013).

Countries are mandated to provide updates on their forest conditions, including the amount of growing stock, to the United Nations as part of international agreements related to climate change, biodiversity preservation, and forest management (Aryal et al., 2023; Cysneiros et al., 2020; McRoberts et al., 2012). This requirement underscores the crucial role of estimating forest growing stocks across different spatial and temporal scales (Gschwantner et al., 2019). In recent years, there has been a surge in global interest in estimating growing stock, driven particularly by concerns over carbon accounting and the need for effective climate change mitigation strategies (Lindner & Karjalainen, 2007; MacFarlane, 2011).

Asna(*Terminalia Tomentosa*) is a deciduous tree species native to the Indian subcontinent from Myanmar in the east to Nepal, India and Bangladesh in the west(Jackson et al., 1994). The plant is commonly found in the forests, especially in the Indian humid regions, including the sub Himalayan tracts of North West provinces, Sikkim and Nepal, also Peninsula Southwards [Khare, 2007]. The plant is uses for many pharmacological properties like antioxidant(Patel eta l 2010).In Nepal, T. *Tomentosa* occurs in Terai and Siwalik, in association with pure s. robusta forest or mixed hardwood forest (Jackson et al., 1994). The excellent timber properties and multiple uses of T. *tomentosa* have been well documented (Jackson et al 1994). Additionally, the government of Nepal has been promoting scientifically sound management practices of *S. robusta* forests of lowlands however, no any management practices has been noted in the case of Terminalia Tomentosa besides managing with Shorea robusta. Traditionally, Terminalia Tomentosa with Sal forests have been managed using a selection system characterized by the selective harvesting of mature trees and maintaining a continuous forest structure (Gautam & Devoe, 2006). In contrast, contemporary scientific management practices now employ planned rotations, regular silvicultural treatments, systematic compartments, and active regeneration as key components(Poudyal et al., 2019).The principle objective is to enhance the social, economic, and environmental benefits derived from forest management with a long-term strategy to fulfill the timber demand of the country (Poudyal et al., 2019).

Despite its significant economic and ecological importance, *T. tomentosa* has been relatively understudied in terms of supporting forest managers' decision-making processes for effective management. The majority of research efforts have been directed towards developing site-specific allometric volume equations for Shorea robusta, an associate species of *T. tomentosa*, with limited attention given to *T. Tomentosa* itself (Subedi, 2017; Shrestha et al., 2018; Silwal et al., 2018; Mandal et al., 2020; Subedi et al., 2021). Additionally, few studies have focused on the biomass of small-sized trees of Shorea robusta, while only one study by Sharma & Pukkala (1990) considered samples from the entire country, Nepal.

These site-specific models often produce varying results and higher prediction errors when applied beyond their study range, and they lack robust sampling and modeling approaches (Chambers et al., 2001; Case & Hall, 2008). Recently, Baral et al. (2021) developed volume functions for the stem and branches of Shorea robusta by consolidating destructively collected samples from four studies. However, these studies solely utilized Shorea robusta trees from natural conditions, failing to adequately represent trees from intensively managed forests. Moreover, none of these studies have developed volume models for *T. Tomentosa*, despite its importance as an associate species of Shorea robusta with commercial value.

Given the differences in growing conditions and management regimes, Terminalia Tomentosa may exhibit distinct tree architectures and stem forms (Parham & Gray, 1984). Furthermore, the limited studies attempting to develop volume equations for *T. tomentosa* or its associated species have often encountered methodological limitations, including inadequate sampling techniques and insufficient modeling approaches. These shortcomings compromise the reliability and applicability of resulting volume models, especially when extrapolated to different forest conditions or management practices (Chambers et al., 2001; Case & Hall, 2008).

Therefore, this study seeks to address these critical gaps in knowledge by developing robust volume models specifically tailored to *T. tomentosa*. By incorporating a comprehensive set of independent variables—including DBH, tree height, and crown dimensions—this research endeavors to provide accurate and reliable estimations of *T. tomentosa* tree volume. Through this endeavor, forest managers and stakeholders will be equipped with essential tools to support informed decision-making processes, ultimately contributing to the sustainable management and conservation of forests and their valuable ecosystem services.

Materials and methods

Study area

The study area is located in the tropical mixed natural hardwood forests of Surkhet district, Nepal, specifically within Bheriganaga Municipality and Barahatal Rural Municipality in Karnali Province, part of the Siwalik range. These forests are primarily dominated by Shorea robusta (Sal) and Terminalia tomentosa (Asna), spanning elevations from 540 to 810 meters above mean sea level. The region experiences a mean annual maximum temperature of 27°C, a mean annual minimum of 15.1°C, and an average annual precipitation of 1391.9 mm (DHM, 2017). The forests exhibit significant ecological diversity, with variations in site quality, stand age, structure, and density. Site quality varies widely, affecting growth conditions, while stand ages range from young regenerating forests to mature stands, reflecting different stages of forest succession. The structure and density of the forest also show extensive variation, from dense undergrowth and thick canopies to more open areas. Additionally, the forests are distributed across various landscape aspects, with different slopes receiving varying amounts of sunlight, wind, and moisture, further contributing to the ecological diversity. This diverse ecological backdrop provides a rich context for studying forest dynamics, biodiversity, and environmental impacts within the Siwalik range, making the area a significant focus for ecological and environmental research.

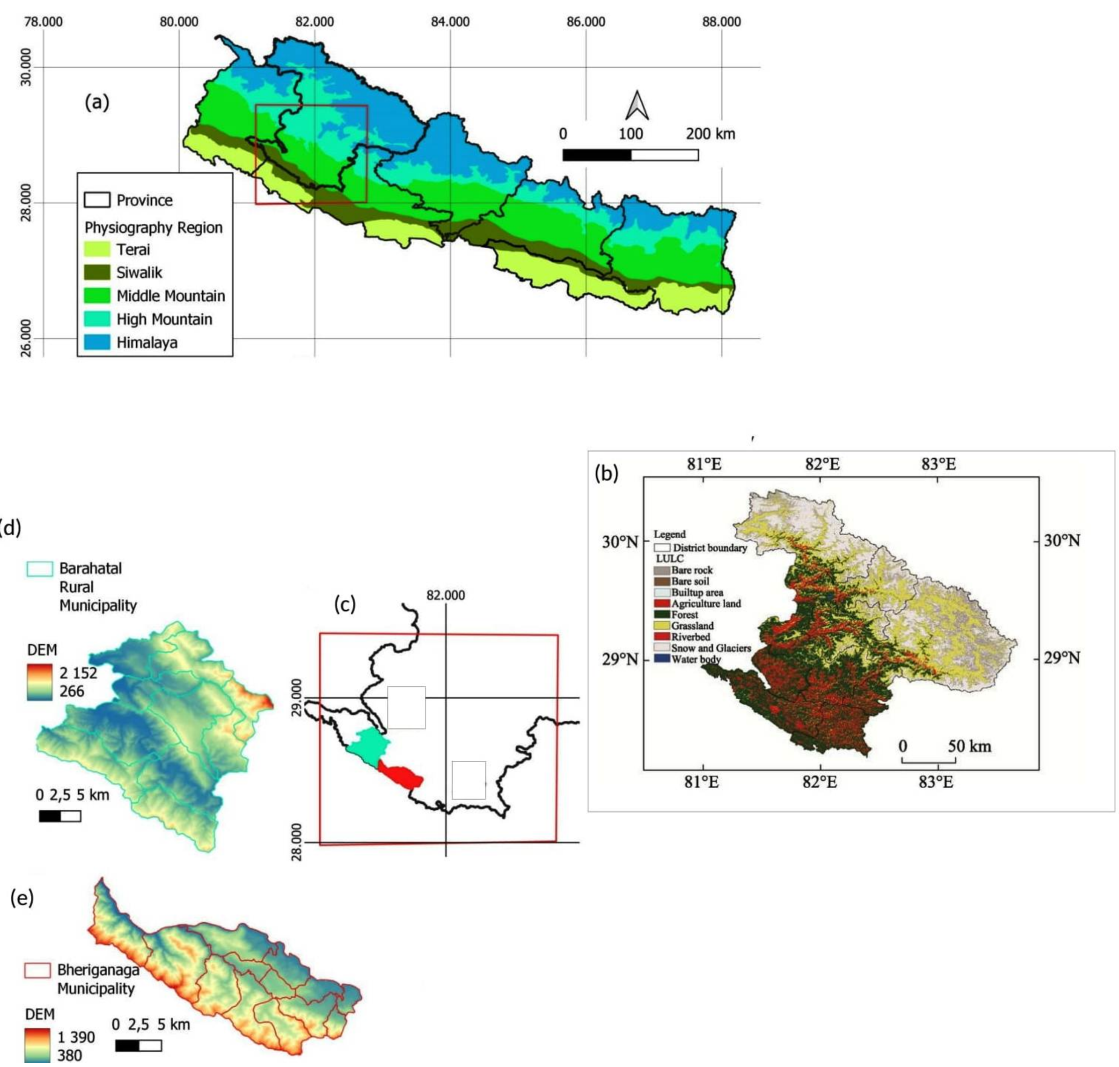

Figure 1: Location map of study area; a) Map of Nepal with Physiographic region and province boundary b) Landuse and landcover map of Karnali Province (Source: ICIMOD, Uddin et al., 2015). *d) Barahatal rural municipality e) Bheriganga Municipality in Surkhet district.*

Sampling and Measurement

A total of 195 healthy, undamaged, and live trees with a diameter at breast height (DBH) of 10 cm or greater were selected for measurement based on subjective criteria, ensuring representativeness of available size and quality classes. Due to legal barriers, destructive sampling was not feasible for this study. Instead, the Dendrometer Criterion RD 1000, known for its accuracy in measuring upper diameters along the stem, was utilized. Tree height was measured using the Vertex instrument, while over bark diameters at 0.3 m, 0.8 m, and 1.3 m from the base of the tree were measured using a

Diameter tape. The remaining portion of the stem was measured at 1.5 m intervals up to the clear tip using the Dendrometer Criterion RD 1000.

Additionally, crown width was assessed by measuring the longest spread and cross spread of each tree, and the average values were considered as the crown width for individual trees. This comprehensive approach to sampling and measurement ensured accurate and detailed data collection for the study of the tropical mixed natural hardwood forests in the Surkhet district.

Calculating Stem Volume

To accurately calculate the total stem volume of each sample tree, we employed three distinct formulas, each tailored to different sections of the tree:

Cylindrical Formula (Eq. 1): Used for calculating the volume of the tree stump.

Smalian's Formula (Eq. 2): Applied to the middle portions of the bole.

Conical Formula (Eq. 3): Used for estimating the volume of the top of the tree.

$$\text{Cylindrical volume} = \frac{\pi D_1^2}{4} \times L(1) \tag{1}$$

$$\text{Volume by Smalian formula} = \left\{\frac{\frac{\pi D_1^2}{4}+\frac{\pi D_2^2}{4}}{2}\right\} \times L(2) \tag{2}$$

$$\text{Cone volume} = \frac{\pi D_1^2}{12} \times L(3) \tag{3}$$

D_1 and D_2 are the diameters at the thick and thin ends, respectively and L is the length of the section.

The relationships between the stem volume and variables such as diameter at breast height (over bark), total height, and crown width are depicted in Figure 3. Table 1 provides a summary of all measured and estimated variables, including form factors.

Table :1 Summary Statistics of measured trees

SN	Variables	Mean	Standard deviation	Minimum	Maximum
1	DBH, cm	38.59	14.21	10.20	70.60
2	Height, m	13.5	4.2	2.8	20.8
3	form factor	0.55	0.13	0.36	0.99
4	Crown width, m	9.67	3.59	1.25	16.9
5	volume	0.95	0.82	0.01	3.53
6	HDR(m/cm)	0.54	0.15	0.35	1.15

Model Estimation and Evaluation

Our initial goal for this study was to incorporate dummy variables into the model to assess the impact of location on variations in stem volume. However, preliminary analysis revealed no significant differences in data across locations thereforefore we merged the data without consideration to the two sites within study area. Consequently, we shifted our focus to modeling by first exploring the graphical patterns of stem volume in relation to DBH, tree height and crown width and HDR (Height Diameter Ratio) (Figure 2). These patterns indicated strong non-linear relationships between stem volume and both DBH and total tree height as well as significant pattern in crown height and HRD (Figure 2). We then identified mathematical functions capable of effectively describing these non-linear relationships (Table 2).

In our study, we leveraged the power of the 'lm' function within the R statistical software package (R Core Team, 2021) to estimate and evaluate our models. This function allowed us to conduct regression analysis, a fundamental tool for modeling relationships between variables. Specifically, we employed Marquardt’s method for optimization, which is a robust algorithm for parameter estimation commonly used in regression analysis.

To assess the performance of our models, we relied on two widely accepted statistical metrics: the root mean square error (RMSE) and the adjusted coefficient of determination (R2adj) (Eq 5 and 6). RMSE provides a measure of the accuracy of model predictions by quantifying the differences between observed and predicted values, while R2adj measures the proportion of variance in the dependent variable that is explained by the independent variables, adjusted for the number of predictors in the model. These metrics are essential for evaluating the goodness-of-fit of regression models and are commonly reported in statistical analyses (Montgomery et al., 2012).

In addition to numerical metrics, we conducted visual inspections of our models by examining residual plots and volume curves. Residual plots allow us to assess the randomness and homogeneity of errors in our model predictions, while volume curves provide graphical representations of the relationships between predictor variables and the response variable. These visualizations offer valuable insights into the appropriateness of our modeling approach and help ensure that our models are grounded in theoretical principles and biological logic (Zeide, 1993).

Our analyses were conducted at a significance level of 5%, adhering to standard practices in statistical hypothesis testing. While model validation is typically an important step in regression modeling, we faced challenges due to the limited size of our dataset. Despite the absence of formal validation, we took measures to ensure the robustness and reliability of our models through rigorous evaluation using statistical metrics and visual inspections.

Although model validation often involves splitting the dataset into training and validation sets, this approach was not deemed suitable for our study due to the similarity in data structure and statistical characteristics between the two subsets. Moreover, resource constraints prevented us from obtaining additional independent data for external validation.

In summary, our comprehensive approach to model estimation and evaluation, combined with the transparency and rigor of our methods, ensures the credibility and trustworthiness of our findings within the constraints of our dataset. We evaluated the fitted models using four common statistical indices:

1. Significance of Estimated Parameters: Unless otherwise specified, a 5% level of significance was used in our analyses to determine the importance of the estimated parameters. (Eq. 4).

2. Root Mean Square Error (RMSE): This metric, the standard deviation of the residuals (prediction errors), ideally equals 0, indicating perfect model predictions. The formula used for RMSE is detailed in Montgomery et al. (2021) (Eq. 5).

3. Adjusted Coefficient of Determination (R^2_adj): This statistic measures the proportion of total variability explained by the model, with higher values indicating better model performance. The calculation for R^2_adj follows the method outlined by Renaud & Victoria-Feser (2010) (Eq. 6).

4. Akaike Information Criterion (AIC): This criterion assesses model quality, with smaller values indicating a better fit. The AIC is computed as described by Burnham & Anderson (2004) (Eq. 7).

$$\text{RSS} = \sum_{i}^{n} (y_i - \hat{y}_i)^2 \tag{4}$$

$$\text{RMSE} = \sqrt[i]{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n-P}} \tag{5}$$

$$R^2 = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y_i})^2} \tag{6}$$

$$\text{AIC} = f(\beta) + 2p \tag{7}$$

Where, n – total non-missing observations; y_i and $\hat{y}_i$– observed value and predicted value of stem volume; $\bar{y}$ - the average value of the observed stem volume; i - the ith observation with value 1, 2,. . .,n; f (β)- negative of the marginal log-likelihood function; β – vector of parameter estimate; p – number of parameters used in the model.

Table 2. Mathematical functions considered to fit data

Designation	Function form	Reference
M1	$v_i = b_1 DBH_i^{b_2} + \varepsilon_i$	Huxley and Tessier (1936)
M2	$v_i = \frac{DBH_i^{\ 2}}{b_1 + b_2 DBH_i} + \varepsilon_i$	Hosoda and Lehara (2010)
M3	$v_i = b_1 exp(-b_2/DBH_i) + \varepsilon_i$	Schumacher (1939)
M4	$v_i = b_1 exp(-b_2/DBH_i^{0.5}) + \varepsilon_i$	After Schumacher (1939)

Note: v_i over bark stem volume of *Terminalia Tomentosa* tree *i*, DBH_i is diameter at breast height (over bark), b_1, b_2 are parameters to be estimated, and ε_i is error term, which is assumed to have normal distribution with mean zero and variance one. $b_1 = \beta_1 H_i^{\beta_2}$ where where H_i is total height of tree i, respectively; *b2*, β_1 *and* β_2 are parameters to be estimated.

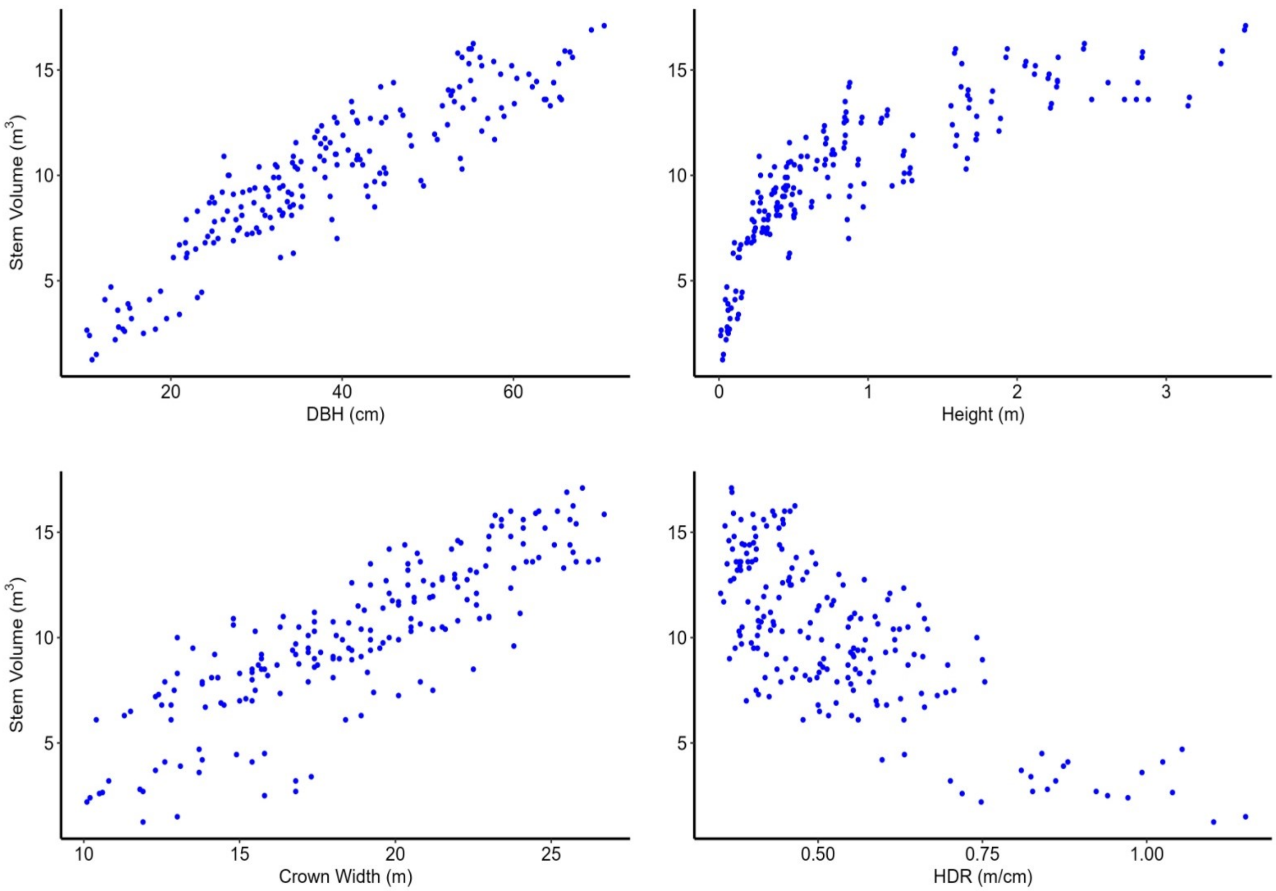

Figure 2. Stem volume plotted against diameter at breast height (DBH)(over bark), total height, Crown width and HDR.

Results

The parameter estimates and fit statistics for all the tested models are presented in Table 3. The estimates for each model, besides model 2, were found to be highly significant ($p < 0.0001$), indicating that the models' parameters are statistically meaningful and reliable. These models demonstrated a robust ability to explain volume variations, with each model accounting for more than 92% of the observed variability in tree volume.

Among the four models evaluated, Models 1, Model3 and Model4 stood out due to their superior performance metrics. These models exhibited the smallest values for the Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE), suggesting they provided the best fit to the data. Their fit statistics were nearly identical, making them top contenders for the best model designation.

Table 3 : Parameter estimates, their p-values, and fit statistics of four fitted functions.

Model	Parameter	Estimate	Std.Error	t_value	p_value	Adj_R2	RMSE	AIC
Model 1	B1	0.00004	0.00001	4.87667	0.00000	0.97166	0.14410	-194.14
	B2	0.28904	0.10739	2.69146	0.00774			
	b2	2.44035	0.07086	34.43968	0.00000			
Model 2	B1	834.72500	300.03125	2.78213	0.00594	0.91849	0.24439	11.87
	B2	0.21801	0.14294	1.52518	0.12886			
	b2	0.00000	3.60580	0.00000	1.00000			
Model 3	B1	3.28648	1.36337	2.41056	0.01687	0.96545	0.15911	-155.50
	B2	0.48709	0.11492	4.23863	0.00003			
	b2	112.94863	3.82331	29.54212	0.00000			
Model 4	B1	53.99967	24.51365	2.20284	0.02880	0.97031	0.14751	-185.02
	B2	0.36942	0.10847	3.40560	0.00080			
	b2	33.41890	1.01865	32.80699	0.00000			

R^2adj = adjusted coefficient of determination; RMSE = root mean squared error; AIC = Akaike information criterion

To further refine our model selection among Model1, Model2 and Model 4, we conducted a detailed analysis of the residual plots and the regression lines generated by these models. This additional scrutiny aimed to assess the adequacy of the models in capturing the patterns in the data and to identify any systematic deviations that might affect the model's predictive accuracy. By examining the residuals, we could identify any potential biases or patterns that were not addressed by the models, thereby ensuring the most accurate and reliable model selection.

The analysis of mean residuals plotted against DBH class and height class for models Model1, Model3, and Model4 revealed no significant systematic trends within the measured data range, indicating that each model performed consistently across different DBH and height classes and effectively captured the variability in stem volume without bias (Fig 3). This consistency across classes underscores the robustness of the models. Further validation of the models' performance is evident in the overlay graph of observed versus predicted stem volume, the regression line of predicted volume against measured volume, and a 1:1 reference line. These graphs demonstrated that the estimated stem volumes closely aligned with the measured stem volumes, with data points clustering around the 1:1 line, indicating that the models provided accurate predictions. The absence of systematic trends in the residuals suggests that none of the models systematically overestimate or underestimate stem volume for specific DBH or height classes, enhancing the models' reliability. The overlay graph analysis showed a strong fit to the data, with regression lines close to the 1:1 reference line, further indicating accurate predictions. The close distribution of data points around the 1:1 line underscored the models' unbiased and independent predictions. Collectively, the residual analysis and overlay graphs demonstrated that all three models effectively described the relationship between DBH, height, and stem volume. This comprehensive evaluation supports the use of any of these models for practical applications in forestry, where accurate volume estimation is crucial, as they have proven to be robust, reliable, and unbiased across the observed data range.

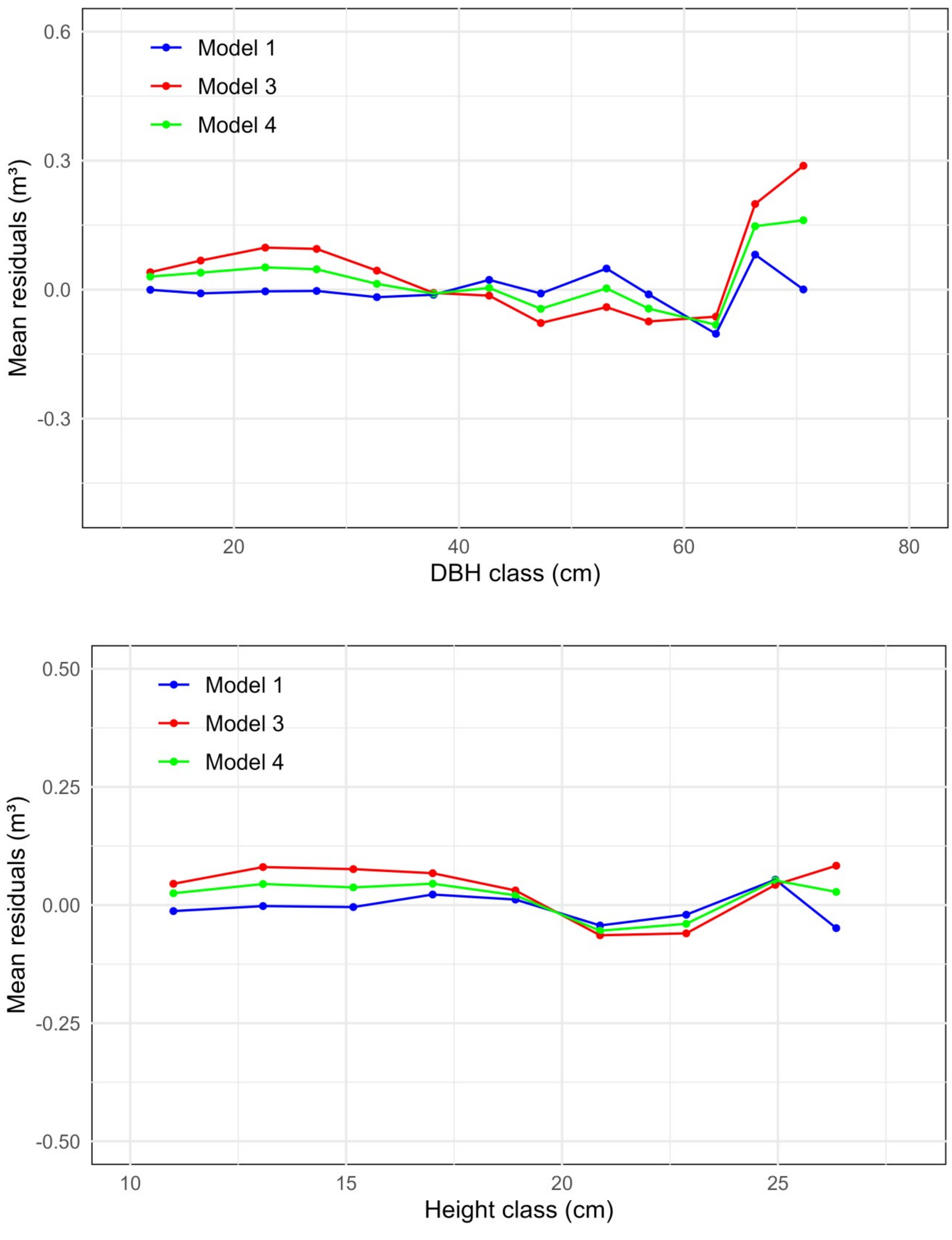

Figure 3. Mean residuals were calculated for models Model1, Model3 and Model4 by DBH class with a 5 cm interval and height class with a 2 m interval.

We further analyzed the model curves generated by the fitted functions (M1, M3, and M4) and superimposed them on the observed volume data (Figure 4). All models demonstrated a promising alignment with biological expectations. The graphical representation indicated a significant impact of total height and DBH on stem volume, highlighting its importance in accurate volume estimation. The consistency and homogeneity of residuals, along with the biological plausibility of the model curves, reinforced the suitability of both the power (M1) and the exponential function (M3 and M4) for predicting stem volume within the observed data range. However, these findings suggest that M1 can effectively capture the complex relationship between DBH, total height, and stem volume, providing reliable predictions that align with biological realities in comparision to other models. The close fit of this model to the empirical data supports its use in practical forestry applications, where accurate volume estimation is essential. Overall, the thorough examination of model curves and their alignment with measured data confirm the robustness and applicability of the power functions in predicting stem volume.

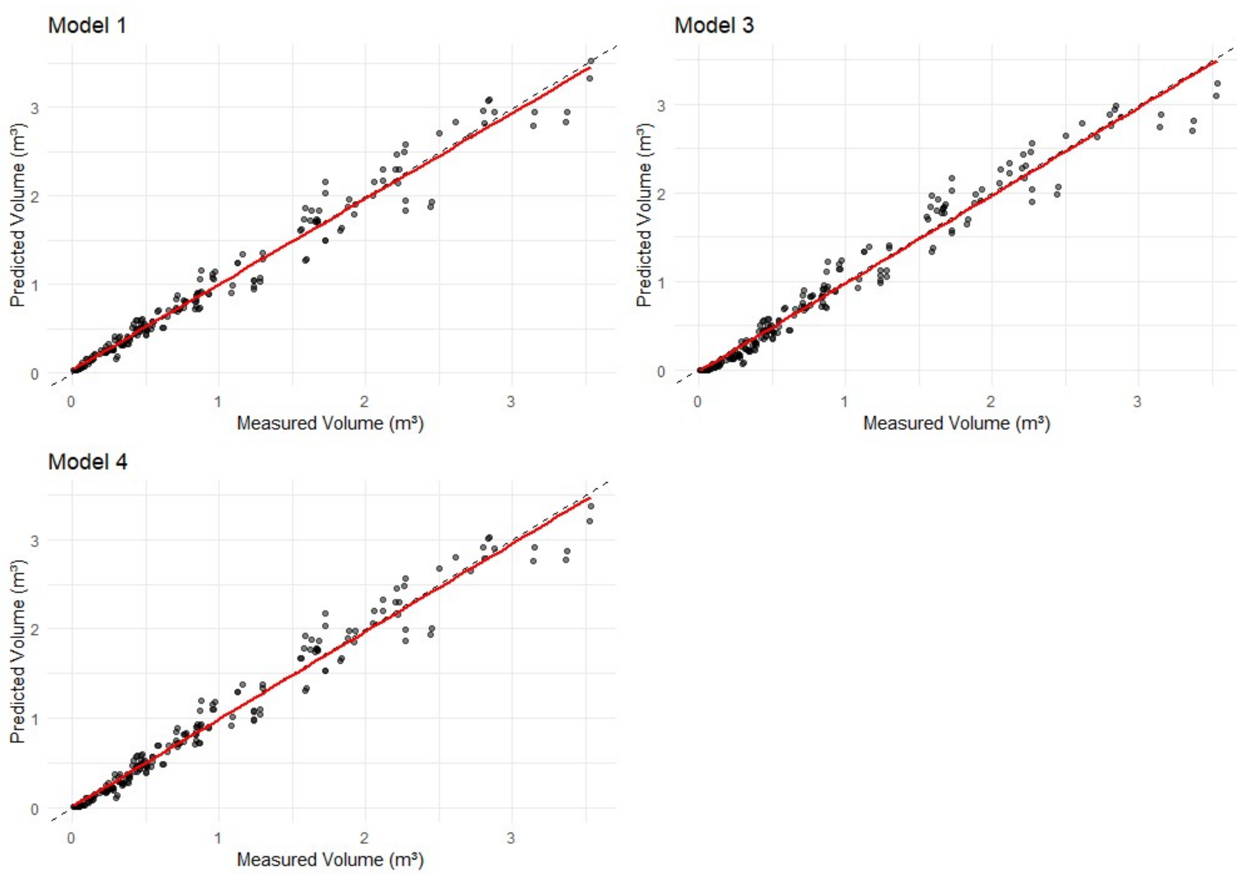

Figure 4: Overlay graphs of straight line (1:1-line, black dashed line) and regression line (red line) produced from the predicted volume (from Model1, Model3 and Model4) regressed against the measured volume.

We analyzed the model curves generated by each model and compared them with the measured stem volume data. Among the models, M1 demonstrated greater biological plausibility compared to the other models. We have only included the models with the most compelling volume curves.These figures illustrate the significant influence of total height on stem volume variations, providing further validation of the chosen models.

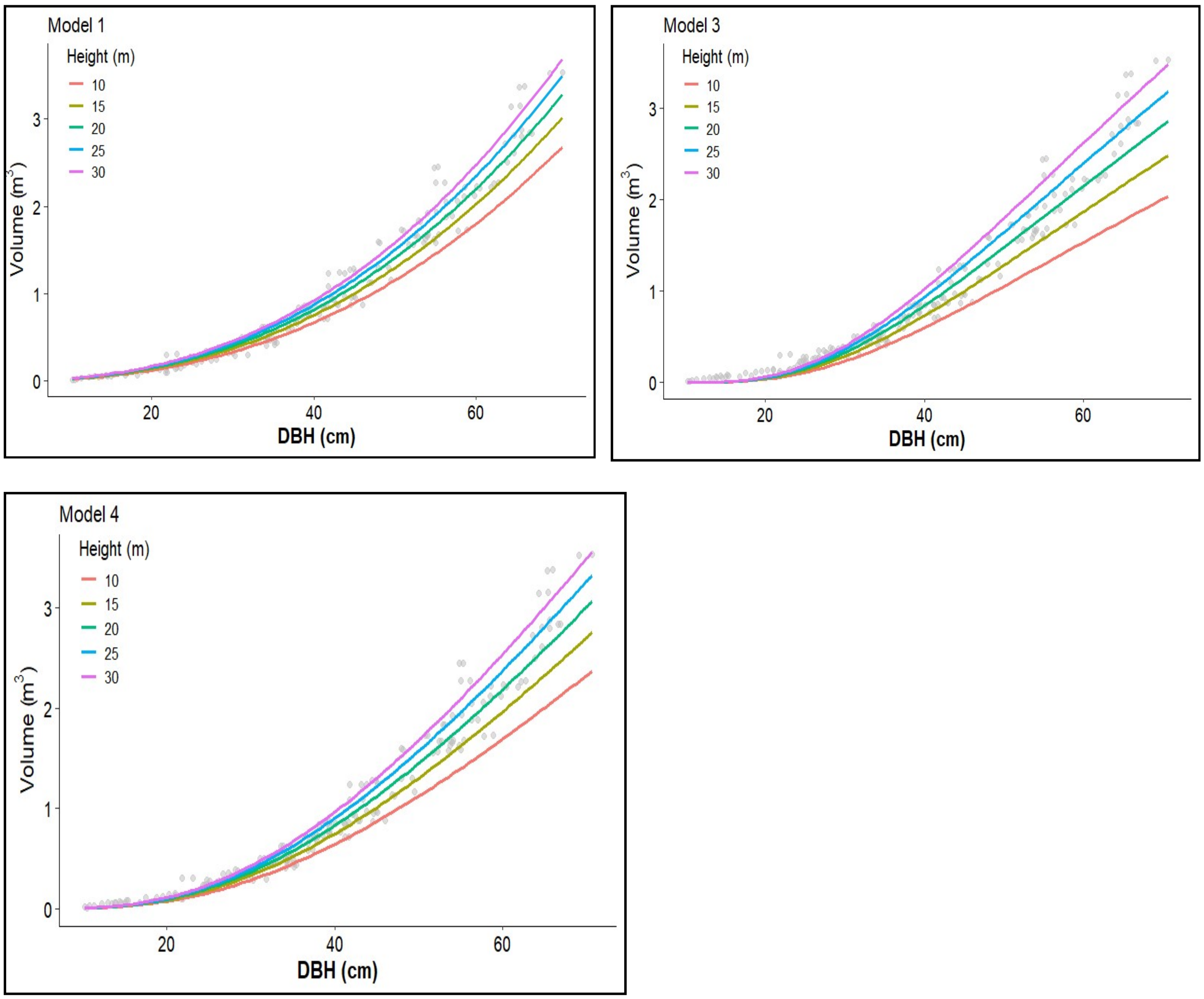

Figure 5. Model curves overlaid on the measured stem volume data for Terminalia tomentosa. With the variation of predictor variable ht of tree from about minimum to maximum values in the measured data, stem volume significantly varied. Model 1 appears biologically more logical than the other.

Comparison of Volume Models with Published Equivalent

In comparing the stem volume models for Terminalia tomentosa developed in this study with the model by Sharma and Pukkala (1990) (Figure 6), we observed that while the predictions from both sets of models are generally close, there are notable differences, particularly at smaller diameters. Specifically, up to a diameter at breast height (DBH) of 60 cm, our models (Model 1, Model 3, and Model 4) exhibit superior fit compared to the Sharma and Pukkala model, which tends to overestimate volume for trees within this size range. This suggests that our models are more accurate for smaller trees and effectively capture the growth dynamics of Terminalia tomentosa up to 60 cm DBH.

Beyond the 60 cm DBH threshold, the predictions from both model sets converge, although our models tend to slightly underestimate volume for larger trees. The reduced discrepancies among models at larger DBHs indicate that, for trees exceeding 60 cm DBH, the volume predictions become more similar across models. This trend underscores the importance of selecting an appropriate model for accurate volume estimation in Terminalia tomentosa, particularly for smaller trees. Differences in model performance at smaller diameters could be attributed to variations in the datasets, tree populations, or growth conditions used in model development.

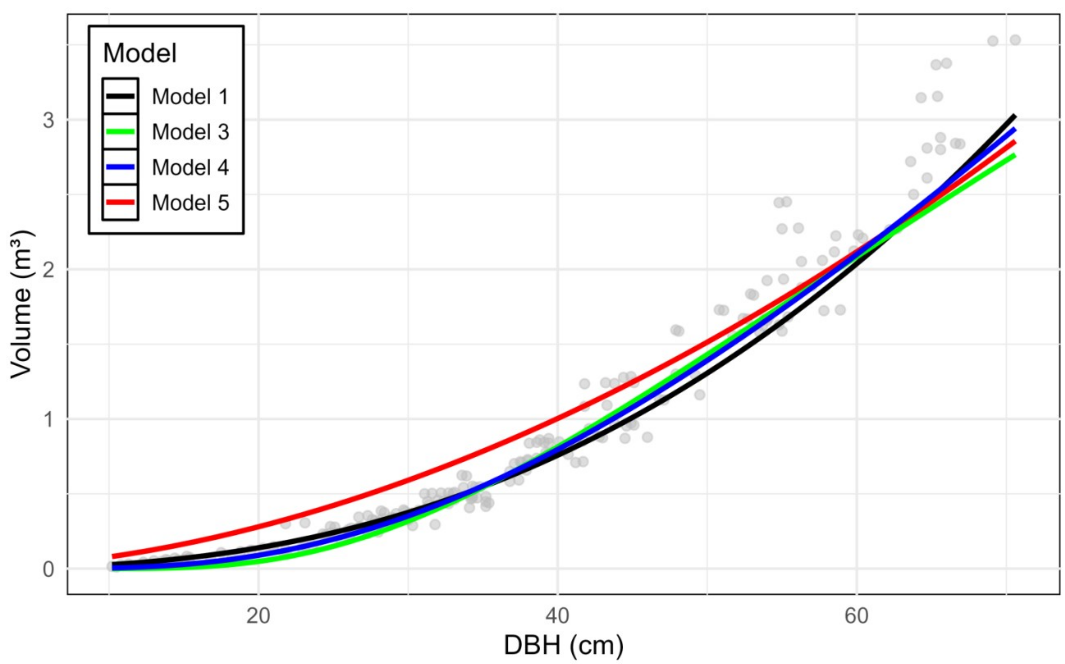

Figure 6: Volume curves of the three models (Model1, Model3 and Model4) from this study, along with the model developed by Sharma & Pukkala (1990)(Model5), overlaid on the observed stem volume data. The black dots represent the observed stem volume data collected in this study

Discussion

Tree volume models are crucial tools for estimating timber volume, forest biomass, and carbon assessment. Accurate volume estimates require robust modeling approaches and comprehensive databases (Chapagain and Sharma, 2021). We developed volume models to predict the stem volumes of individual trees growing in the natural forests of *terminalia tomentosa* in Karnali province, (Figure 1). The models for *terminalia tomentosa* are designed to predict outside bark stem volumes.

Our dataset includes a wide range of mature trees covering all potential variabilities of the main tree variables (Table 1, Figure 3). This comprehensive data is the foundation for developing robust models. The chosen candidate functions (Table 2) are flexible enough to describe a wide range of variations in the response variable of interest, which in our case is stem volume. These functions have been frequently used by many modelers to build various forestry models (Aryal et al 2023, Hosoda and Iehara, 2010; Huxley and Teissier, 1936; Schumacher, 1939; Sharma et al., 2016; Shrestha et al., 2017).

Choosing the correct form of the candidate function to fit the data is a critical step in building a robust model. This decision must align with the data pattern observed. The nonlinear functions selected in our study effectively described the observed nonlinearity patterns (Figure 2) and exhibited small deviations of residuals from zero (Figure 3). This indicates the effectiveness and reliability of our models in predicting stem volume accurately

Although we fitted various functions of differing complexities, we identified DBH as the most critical attribute explaining most of the volume variation, consistent with findings from other studies (Neumann et al., 2016; Subedi, 2017; Shrestha et al., 2018). For example, our models that used only DBH as a predictor variable accounted for 87-90% of the variations in stem volume. When height was added to the models, the explained variability increased to 92-96%. This modest increase is due to the strong correlation between DBH and tree height (Lee et al., 2017). However, on a regional scale like ours, environmental heterogeneity can cause significant height variations within the same diameter class (Mauya et al., 2014; Mensah et al., 2017). Thus, models relying solely on DBH might provide biased estimates.

Incorporating additional variables such as height to crown base, tree slenderness, and crown dimensions has been shown to improve accuracy in previous studies (Mauya et al., 2014; Silwal et al., 2018; Baral et al., 2021). However, this complexity can also pose practical challenges. Field measurements of these additional variables can be cumbersome, potentially limiting the models' applicability. Our primary objective was to develop a straightforward volume equation suitable for regional application, targeting Divisional Forest Offices. In this context, simpler models are more practical and effective, aligning with the operational needs and constraints of governmental agencies. Despite their simplicity, models using DBH and height can accurately describe the allometric attributes of stem volume, especially when developed and validated at a regional scale (Oliveira et al., 2018).

Our dataset represented two distinct sites within surkhet district of Karnali province, and we initially aimed to assess site-specific variations in tree volume by introducing site as a categorical dummy variable in our modeling framework. However, an examination of scatter plots depicting the relationships between tree volume and predictor variables revealed no consistent or systematic differences among the data sources (Figure 2). Similarly, Baral et al. (2021) reported minimal variations between data sources while developing a generic volume equation using data from various parts of Nepal. This suggests that a regionally generalized model can be both effective and practical, even when developed with diverse datasets.

To our knowledge, this study represents the first attempt to develop stem volume functions for *Terminalia tomentosa* at a local scale , utilizing samples collected from managed forests across Karnali regions of Nepal. Our results indicate a strong predictability performance for the both power function and exponential function. However, the power function demonstrates superior fit statistics, with lower AIC and RMSE values. When considering other volume or biomass equations developed for various species, it is evident that both the power form (Wan-Mohd-Jaafar et al., 2017; BK et al., 2019) and the fractional form (Vanclay, 1994; Hosoda & Iehara, 2010; Subedi & Sharma, 2012) often yield the best performance. The fit statistics for our models are further validated by the graphical representations of residuals and the curves of predicted versus measured volumes (Figure 5).

The smaller residual variations observed for smaller trees (Figure 3) suggest that our models are particularly precise in estimating volumes for these trees. This precision may also be partly due to the limited number of observations available for larger trees. Figure 5 illustrates the significant impact of tree height in both power and exponential functions, as evidenced by the clear differentiation in predicted stem volumes even for trees with the same DBH. Given the negligible differences between the power and exponential functions, both models are suitable for estimating tree volume. The robustness of these models is supported by their ability to adequately cover the range of data, providing reliable predictions for trees across varying sizes and conditions.

The absence of systematic trends in the residuals (Figure 4) indicates the model's accuracy and reliability. This lack of bias in the residuals confirms that the models effectively capture the underlying patterns in the data. Moreover, the distinct separation of the curves generated by the final models within the observed data range, even for trees with the same DBH, underscores the substantial influence of additional predictor variables (Figure 5). These results highlight the models' capability to account for various factors affecting stem volume, beyond just DBH, ensuring a more comprehensive and precise estimation. The significant effects of covariate predictors such as tree height and crown width contribute to the models' robustness, allowing them to differentiate accurately between trees with similar DBH but differing in other attributes. This differentiation is crucial for accurately predicting stem volumes across a wide range of tree sizes and conditions, ultimately enhancing the models' applicability and effectiveness in practical forestry assessments.

Modelers often opt to use Diameter at Breast Height (DBH) as the sole predictor in stem volume models due to its ability to explain approximately 75% of the variation in stem volumes, thus keeping the models relatively simple. However, the limitation of these models lies in their reduced accuracy when trees of similar DBH exhibit varying heights and crown sizes—a common scenario in forest stands of any size. To address this limitation, researchers have found that including tree height as a covariate predictor significantly improves the precision of the models (Lee et al., 2017).

Moreover, incorporating additional predictors such as Height-to-DBH Ratio (HDR), which indicates tree slenderness, and crown size, a measure of tree vigor and health, can further enhance model accuracy and broaden its applicability across different forest conditions. In our study, we expanded our models by adding total height as a covariate. This adjustment notably enhanced the fit of our volume models, underscoring the considerable influence of these covariates on the variations in stem volume.

While crown size is expected to exert a significant influence on stem volume variations, our study could not verify this due to the unpredictable pattern of crown information in our dataset as this was due to lack of instruments for the measurement of crownwidth. Future research efforts focusing on including crown size data would likely provide further insights into its impact on stem volume predictions and forest management strategies.

We utilized two common statistical measures to evaluate forestry models. Model validation, crucial for confirming model reliability, was not performed due to the absence of external independent data. Additionally, we did not employ data splitting, which divides data into fitting and validation sets, because our datasets shared similar characteristics and were derived from the same tree population and sampling methods as noted in several studies (Chapagain and Sharma, 2021; Hirsch, 1991; Kozak and Kozak, 2003; Yang et al., 2004; Zhang, 1997).

To enhance statistical robustness, we advocate using the entire dataset for estimating model parameters, which yields more stable estimates with smaller standard errors. Conversely, splitting the data into smaller subsets for validation (e.g., 1/3, 1/2, 1/4 sets or k-folds) often leads to overestimation of errors due to the reduced size of the fitting dataset (Chapagain and Sharma, 2021; Hirsch, 1991; Kozak and Kozak, 2003; Yang et al., 2004; Zhang, 1997). Therefore, the preferable alternative is validating models with external independent datasets (Crecente-Campo et al., 2010; Sharma et al., 2011; Sharma et al., 2019), a step we plan for future validations with additional data.

Given the diverse modeling approaches, predictor variables, and dataset sizes across forest modeling studies, direct comparison with previous models may not be robust. However, some comparison against earlier studies (Figure 6) was conducted, such as with models by Sharma and Pukkala (1990), despite uncertainties in their accuracy due to dated data collection methods.

Our comparisons revealed systematic overestimation issues with existing volume models (Sharma and Pukkala, 1990) upto DBH of 60 cm when applied to our study forests (Figure 1), highlighting the necessity for developing new, species-specific volume models based on comprehensive local data covering specific growth conditions.

The stem volume models (Model 1) presented exhibit both biological plausibility and statistical flexibility suitable for various applications such as quantifying growing stock, carbon accounting, timber valuation, growth and yield modeling, and environmental analysis. This model incorporate key tree factors (diameter, height, crown size, age), external factors (site quality, topography, climate), and stand factors (development stage, structure, competition stress), which significantly influence stem volume. Including these predictor variables can enhance model accuracy and broaden its applicability, albeit increasing complexity. Advanced software tools like SAS and R facilitate handling such complexities.

While our models demonstrate robust biological foundations (Figure 5) and statistical reliability (small standard errors, Table 3), their generalizability beyond the specific small forest area studied (Figure 1) in the Karnali province may be limited. Variability in growth due to topography, soil, climate, and forest density may differ across larger geographical extents. Therefore, our models are best applied as a foundation within similar forest contexts and require rigorous testing before extrapolating to broader distributions of the target species, even within the Karnali province.

For volume modeling , proper handling of dummy variables is crucial. Future enhancements could involve recalibrating models with additional data covering wider species distributions across Karnali and beyond, and validating these models against independent datasets. Validation, a critical modeling step for enhancing credibility, was not conducted through data splitting due to concerns that this method may not significantly differ from fitting models with the entire dataset, potentially leading to overestimation of errors.

To ensure robust predictive performance, future efforts should focus on testing models against independent datasets representing diverse geographical and stand-level attributes, which was constrained in this study due to resource limitations. This approach aligns with best practices in model validation (Vanclay, 1994; Vanclay & Skovsgaard, 1997; Yang et al., 2004) and ensures confidence in model applicability beyond the study's immediate scope

Conclusion

Allometric stem volume models were meticulously developed for *Terminalia tomentosa*, a significant timber species in Karnali Province, Nepal. These models were constructed using comprehensive data encompassing a diverse range of individuals, including mature trees, and employed Diameter at Breast Height (DBH) and total height. Remarkably, the models collectively accounted for over 92% of the variation in stem volume, demonstrating robust fit statistics particularly strong for *Terminalia tomentosa*.

The proposed volume models is not only biologically sound but also statistically robust, rendering them suitable for precise applications such as quantifying growing stock, carbon accounting, timber valuation, growth and yield modeling, and environmental analysis within Karnali Province and similar regions. However, it is crucial to exercise caution when applying these models to forest conditions that differ significantly from those represented in the original dataset.

To further enhance prediction accuracy, future research efforts should prioritize recalibrating the models using additional data collected from broader distributions of *Terminalia tomentosa* across Karnali Province and potentially beyond. Furthermore, rigorous validation of these models against independent datasets would bolster confidence in their applicability across diverse forest ecosystems.

Given the pivotal role of *Terminalia tomentosa* in scientifically managed lowland forests, our volume equations serve as indispensable tools for assessing growth and yield modeling, estimating growing stock, and conducting carbon accounting, thereby facilitating sustainable forest management practices. Continual development and testing of allometric equations are essential; thus, we recommend that future researchers expand sample sizes to encompass a wider geographic range and management scenarios. Additionally, including additional variables that capture site and stand-level attributes will further refine and broaden the applicability of volume equations for *Terminalia tomentosa*.

References

Aryal, K. R., Chapagain, T. R., Basukala, R. K., Khadka, S., Chaudhary, G., Budha, R. K., ... & Sharma, R. P. (2023). Allometric tree volume models for Pinus roxberghii and Cedrus deodara in Karnali Province, Nepal. Forest Ecology and Management, 546, 121364.

Baral, S. G., Vacik, H., Chhetri, B. B. K., & Gauli, K. (2018). The pertinent role of forest inventory in making choice of silvicultural operations in community forests of Nepal. *Banko Janakari*, *4*, 65–75.

Baral, S., Neumann, M., Basnyat, B., Gauli, K., Gautam, S., Bhandari, S. K., & Vacik, H. (2020). Form factors of an economically valuable Sal tree (*Shorea robusta*) of Nepal. *Forests*, *11*(7), 754.

Baral, S., Neumann, M., Basnyat, B., Sharma, R. P., Silwal, R., Shrestha, H. L., Subedi, T., & Vacik, H. (2021). Volume functions for *Shorea robusta* Gaertn. in Nepal. *Forestry: An International Journal of Forest Research*, *95*(3), 405–415.

Basuki, T. M., Van Laake, P. E., Skidmore, A. K., & Hussin, Y. A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management*, *257*(8), 1684–1694.

Bhandari, S. K., & Chhetri, B. B. K. (2020). Individual-based modelling for predicting height and biomass of juveniles of *Shorea robusta*. *Austrian Journal of Forest Science*, *137*(2), 133–160.

BK, R. B., Sharma, R. P., & Bhandari, S. K. (2019). A generalized aboveground biomass model for juvenile individuals of Rhododendron arboreum (SM.) in Nepal. *Cerne*, *25*(2), 119–130.

Buckley, T.N., Cescatti, A. and Farquhar, G.D., 2013. What does optimization theory actually predict about crown profiles of photosynthetic capacity when models incorporate greater realism? Plant, Cell & Environment, 36(8): 1547-1563.

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: understanding AIC and BIC in model selection. *Sociological Methods & Research*, *33*(2), 261–304.

Case, B. S., & Hall, R. J. (2008). Assessing prediction errors of generalized tree biomass and volume equations for the boreal forest region of west-central Canada. *Canadian Journal of Forest Research*, *38*(4), 878–889.

Chambers, J. Q., dos Santos, J., Ribeiro, R. J., & Higuchi, N. (2001). Tree damage, allometric relationships, and above-ground net primary production in central Amazon forest. *Forest Ecology and Management*, *152*(1–3), 73–84.

Chapagain, Tolak R, Sharma, R. P., & Bhandari, S. K. (2014). Modeling above-ground biomass for three tropical tree species at their juvenile stage. *Forest Science and Technology*, *10*(2), 51–60.

Chapagain, Tolak Raj, & Sharma, R. P. (2021). Modeling form factors for sal (*Shorea robusta* Gaertn.) using tree and stand measures, and random effects. *Forest Ecology and Management*, *482*, 118807.

Chaturvedi, R. K., Raghubanshi, A. S., & Singh, J. S. (2012). Biomass estimation of dry tropical woody species at juvenile stage. *The Scientific World Journal*, *2012*.

DFRS. (2014). Terai Forests of Nepal. In *Forest Resource Assessment Nepal Project (FRA). Department of Forest Research and Survey.*

DFRS. (2015). State of Nepal's forests. *Forest Resource Assessment (FRA). Department of Forest Resource and Survey, Kathmandu*.

DHM. (2017). Observed climate trend analysis in the districts and physiographic regions of Nepal (1971–2014). *Department of Hydrology and Meteorology, Kathmandu*, *1*, 74.

Edwards Jr, T. C., Cutler, D. R., Zimmermann, N. E., Geiser, L., & Moisen, G. G. (2006). Effects of sample survey design on the accuracy of classification tree models in species distribution models. *Ecological Modelling*, *199*(2), 132–141.

Eerikäinen, K., Hinh, V. T., Huy, B., Khanh, D. C., Khoa, P. V, Khoi, N. K., Lung, N. N., Mandal, R. A., Phuong, V. T., & Pokharel, Y. P. (2012). A review of the applicability of existing tree and forest characteristics prediction models to forest inventory in Vietnam and Nepal. *Finnish Forest Research Institute*, *978-951-40-2373–6*.

Gautam, K. H., & Devoe, N. N. (2006). Ecological and anthropogenic niches of sal (*Shorea robusta* Gaertn. f.) forest and prospects for multiple-product forest management–a review. *Forestry*, *79*(1), 81–101.

Gier, A. de. (2003). A new approach to woody biomass assessment in woodlands and shrublands. *Geoinformatics for Tropical Ecosystems*, 161–198.

Gower, S. T., Kucharik, C. J., & Norman, J. M. (1999). Direct and indirect estimation of leaf area index, fAPAR, and net primary production of terrestrial ecosystems. *Remote Sensing of Environment*, *70*(1), 29–51.

Hirsch, R. P. (1991). Validation samples. *Biometrics*, *47*(3), 1193–1194.

Hosoda, K., & Iehara, T. (2010). Aboveground biomass equations for individual trees of *Cryptomeria japonica, Chamaecyparis obtusa* and *Larix kaempferi* in Japan. *Journal of Forest Research*, *15*, 299–306.

Huxley, J. S., & Teissier, G. (1936). Terminology of relative growth. *Nature*, *137*(3471), 780–781.

Jackson, J. K., Stapleton, C. M. A., & Jeanrenaud, J.-P. (1994). Manual of afforestation in Nepal. *Forest Research and Survey Centre, Ministry of Forest and Soil Conservation*, *2nd editio*.

Joshi, K. (2003). Leaf flavonoid patterns and ethnobotany of *Shorea robusta* Gaertn,(Dipterocarpaceae). *Proceedings of International Conference on Women, Science and Technology for Poverty Alleviation*, 101–107.

Kershaw Jr, J. A., Ducey, M. J., Beers, T. W., & Husch, B. (2016). Forest mensuration. In *John Wiley & Sons, Oxford, U.K.* (p. 630pp.).

Khare CP. The Indian Medicinal Plants-An illustrated dictionary. Springer India; 2007: 655-6. 4. Jain VC,

Koirala, A., Kizha, A. R., & Baral, S. (2017). Modeling height-diameter relationship and volume of teak (*Tectona grandis* LF) in Central Lowlands of Nepal. *Journal of Tropical Forestry and Environment*, *7*(1), 28–42.

Kora, A. J. (2019). Leaves as dining plates, food wraps and food packing material: Importance of renewable resources in Indian culture. *Bulletin of the National Research Centre*, *43*(1), 1–15.

Kozak, A., & Kozak, R. (2003). Does cross validation provide additional information in the evaluation of regression models? *Canadian Journal of Forest Research*, *33*(6), 976–987.

Lee, D., Seo, Y., & Choi, J. (2017). Estimation and validation of stem volume equations for *Pinus densiflora, Pinus koraiensis*, and *Larix kaempferi* in South Korea. *Forest Science and Technology*, *13*(2), 77–82.

Lucas, R. M., Cronin, N., Lee, A., Moghaddam, M., Witte, C., & Tickle, P. (2006). Empirical relationships between AIRSAR backscatter and LiDAR-derived forest biomass, Queensland, Australia. *Remote Sensing of Environment*, *100*(3), 407–425.

Malata, H., Ngulube, E. S., & Missanjo, E. (2017). Site specific stem volume models for *Pinus patula* and *Pinus oocarpa*. *International Journal of Forestry Research*, *2017*(10), 1–6.

Mandal, R. A., Khadka, G. B., Shrestha, M., Sah, S. P., & Lamichhane, A. (2020). Modeling the diameter at breast height (DBH) with height and volume of *Shorea robusta* using destructive method: A study from Banke District, Nepal. In *License This work is licensed under a Creative Commons Attribution 4.0 International License.* (Vol. 56, Issue 293, pp. 239–253). Discovery.

Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. *Journal of the Society for Industrial and Applied Mathematics*, *11*(2), 431–441.

Mauya, E. W., Mugasha, W. A., Zahabu, E., Bollandsås, O. M., & Eid, T. (2014). Models for estimation of tree volume in the miombo woodlands of Tanzania. *Southern Forests: A Journal of Forest Science*, *76*(4), 209–219.

Mensah, S., Veldtman, R., & Seifert, T. (2017). Allometric models for height and aboveground biomass of dominant tree species in South African Mistbelt forests. *Southern Forests: A Journal of Forest Science*, *79*(1), 19–30.

Methol, R. (2001). Comparisons of approaches to modelling tree taper, stand structure and stand dynamics in forest plantations. *[Doctoral Thesis] School of Forestry, University of Canterbury, New Zealand.*

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). Introduction to linear regression analysis. In *John Wiley & Sons*.

Muhairwe, C. K. (1999). Taper equations for *Eucalyptus pilularis* and *Eucalyptus grandis* for the north coast in New South Wales, Australia. *Forest Ecology and Management*, *113*(2–3), 251–269.

Nepal, F. R. A. (2015). State of Nepal's forests. *Forest Resource Assessment (FRA)*.

Neumann, M., Moreno, A., Mues, V., Härkönen, S., Mura, M., Bouriaud, O., Lang, M., Achten, W. M. J., Thivolle-Cazat, A., & Bronisz, K. (2016). Comparison of carbon estimation methods for European forests. *Forest Ecology and Management*, *361*, 397–420.

Oliveira, L. Z., Klitzke, A. R., Fantini, A. C., Uller, H. F., Correia, J., & Vibrans, A. C. (2018). Robust volumetric models for supporting the management of secondary forest stands in the Southern Brazilian Atlantic Forest. *Anais Da Academia Brasileira de Ciências*, *90*, 3729–3744.

Özçelik, R. (2008). Comparison of formulae for estimating tree bole volumes of *Pinus sylvestris*. *Scandinavian Journal of Forest Research*, *23*(5), 412–418.

Özçelik, R., Diamantopoulou, M. J., Brooks, J. R., & Wiant Jr, H. V. (2010). Estimating tree bole volume using artificial neural network models for four species in Turkey. *Journal of Environmental Management*, *91*(3), 742–753.

Parham, R. A., & Gray, R. L. (1984). Formation and structure of wood. *In The Chemistry of Solid Wood (R. Rowell, Ed.) Chapter 1. ACS, Washington, D.C.*

Patel NM, Shah DP, Patel PK, Joshi BH. Antioxidant and antimicrobial activities of Terminalia crenulata Roth bark. Pharmacologyonline2010; 2:204- 17

Pérez, D. (2003). Heartwood, sapwood and bark content, and wood dry density of young and mature teak (*Tectona grandis*) trees grown in Costa Rica. *Silva Fenniea*, *37*, 45–54.

Poudyal, B. H., Maraseni, T., & Cockfield, G. (2019). Scientific forest management practice in Nepal: Critical reflections from stakeholders' perspectives. *Forests*, *11*(1), 27.

R Core Team. (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Renaud, O., & Victoria-Feser, M.-P. (2010). A robust coefficient of determination for regression. *Journal of Statistical Planning and Inference*, *140*(7), 1852–1862.

Schumacher, F. X. (1939). A new growth curve and its application to timber yield studies. *Journal of Forestry*, *37*(11), 819–820.

Segura, M., & Kanninen, M. (2005). Allometric models for tree volume and total aboveground biomass in a tropical humid forest in Costa Rica. *Biotropica*, *37*(1), 2–8. https://doi.org/10.1111/j.1744-7429.2005.02027.x

Sharma, E. R., & Pukkala, T. (1990). Volume tables for forest trees of Nepal. In *Vol. 48. Forest Survey and Statistics Division; Ministry of Forests and Soil Conservation, His Majesty Government of Nepal: Kathmandu, Nepal, 1990.*

Sharma, R. P. (2011). Allometric models for total-tree and component-tree biomass of *Alnus nepalensis* D. Don in Nepal. *Indian Forester*, *137*(12), 1386–1390.

Shrestha, H. L., Kafle, M. R., Khanal, K., & Mandal, R. A. (2018). Developing local volume tables for three important tree species in Nawalparasi and Kapilvastu districts. *Banko Janakari*, *27*, 84–91.

Silwal, R., Baral, S. K., & Chhetri, B. B. K. (2018). Modeling taper and volume of Sal (*Shorea robusta* Gaertn. f.) trees in the western Terai region of Nepal. *Banko Janakari*, *4*, 76–83.

Skovsgaard, J. P., & Vanclay, J. K. (2013). Forest site productivity: a review of spatial and temporal variability in natural site conditions. *Forestry*, *86*(3), 305–315.

Spurr, S. H. (1952). Forest inventory. *Ronald Press Co., New York*.

Subedi, M. R., & Sharma, R. P. (2012). Allometric biomass models for bark of *Cinnamomum tamala* in mid-hill of Nepal. *Biomass and Bioenergy*, *47*, 44–49.

Subedi, T. (2017). Volume models for Sal (*Shorea robusta* Gaertn.) in far-western Terai of Nepal. *Banko Janakari*, *27*(2), 3–11.

Subedi, Thakur, Bhandari, S. K., Pandey, N., Timilsina, Y. P., & Mahatara, D. (2021). Form factor and volume equations for individual trees of *Shorea robusta* in Western low land of Nepal. *Aust J For Sci*, *138*(3), 143–166.

Tewari, V. P., & Singh, B. (2018). Total wood volume equations for *Tectona grandis* Linn F. stands in Gujarat, India. *Journal of Forest and Environmental Science*, *34*(4), 313–320.

Thangjam, U., Sahoo, U. K., Thong, P., & Sileshi, G. W. (2019). Developing tree volume equation for *Parkia timoriana* grown in home gardens and shifting cultivation areas of North-East India. *Forests, Trees and Livelihoods*, *28*(4), 227–239.

Uddin, K., Chaudhary, S., Chettri, N., Kotru, R., Murthy, M., Chaudhary, R. P., ... & Gautam, S. K. (2015). The changing land cover and fragmenting forest on the Roof of the World: A case study in Nepal's Kailash Sacred Landscape. Landscape and Urban Planning, 141, 1-10.

Ulak, S., Ghimire, K., Gautam, R., Bhandari, S. K., Poudel, K. P., Timilsina, Y. P., Pradhan, D., & Subedi, T. (2022). Predicting the upper stem diameters and volume of a tropical dominant tree species. *Journal of Forestry Research*, *33*(6), 1725–1737.

Vanclay, J. K. (1994). Modelling forest growth and yield: applications to mixed tropical forests. In *CAB International , Wallingford*. Southern Cross University.

Vanclay, J. K., & Skovsgaard, J. P. (1997). Evaluating forest growth models. *Ecological Modelling*, *98*(1), 1–12.

Ver Planck, N. R., & MacFarlane, D. W. (2014). Modelling vertical allocation of tree stem and branch volume for hardwoods. *Forestry: An International Journal of Forest Research*, *87*(3), 459–469.

Von Bertalanffy, L. (1949). Problems of organic growth. *Nature*, *163*(4135), 156–158.

Wagle, B. H., & Sharma, R. P. (2011). Modelling height-diameter relationship for *Pinus wallichiana* trees for Lete and Kunjo of Mustang district. *Banko Janakari*, *21*(2), 13–23.

Wan-Mohd-Jaafar, W. S., Woodhouse, I. H., Silva, C. A., Omar, H., & Hudak, A. T. (2017). Modelling individual tree aboveground biomass using discrete return lidar in lowland dipterocarp forest of Malaysia. *Journal of Tropical Forest Science*, *29*(4), 465–484.

Wang, Y.-F., Yue, T.-X., Du, Z.-P., & Zhao, M.-W. (2015). Improving the accuracy of the height–diameter equation using the classified factors method. *Environmental Earth Sciences*, *74*(8), 6471–6480.

Wu, C.-F. (1981). Asymptotic theory of nonlinear least squares estimation. *The Annals of Statistics*, *9*(3), 501–513.

Yang, Y., Monserud, R. A., & Huang, S. (2004). An evaluation of diagnostic tests and their roles in validating forest biometric models. *Canadian Journal of Forest Research*, *34*(3), 619–629.

Zeide, B. (1993). Analysis of growth equations. *Forest Science*, *39*(3), 594–616.

Zianis, D., Muukkonen, P., Mäkipää, R., & Mencuccini, M. (2005). Biomass and stem volume equations for tree species in Europe. In *Silva Fennica Monographs* (p. p.63).