Allometric tree volume models for Pinus roxberghii and Cedrus deodara in Karnali Province, Nepal

Article *in* Forest Ecology and Management · October 2023

10 authors, including:

Kamal Raj Aryal
Government of Nepal

Tolak Raj Chapagain
Ministry of Forests and Environment Lumbini Province, Nepal

Ram P. Sharma
Institute of Forestry Tribhuwan University

Forest Ecology and Management 546 (2023) 121364

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Allometric tree volume models for *Pinus roxberghii* and *Cedrus deodara* in Karnali Province, Nepal

Kamal Raj Aryal[a,*], Tolak Raj Chapagain[b], Rajendra Kumar Basukala[a], Sabitra Khadka[a], Gopiram Chaudhary[a], Ram Krishna Budha[a], Hari Adhikari[c], Dinesh Jung Khatri[d], Upendra Aryal[b], Ram P. Sharma[a]

[a] *Forest Research and Training Centre, Surkhet-21700, Karnali Province, Nepal*
[b] *Ministry of Forests and Environment, Lumbini Province, Deukhuri, Nepal*
[c] *AFRY Management Consulting Oy, Jaakonkatu 3, 01620 Vantaa, Finland*
[d] *Division Forest Office, Jumla, Karnali Province, Nepal*

ARTICLE INFO

Keywords:
Destructive sampling
Tree volume modeling
Nonlinear regression
Dummy variable modeling
Model validation
Western Nepal

ABSTRACT

Effective forest management is based on information, such as current growing stock and its future state, which is provided by various forestry models, including tree volume models. Tree volume models are essential tools for estimating growing stock, carbon accounting, timber valuation, identifying forest stands to harvest, growth and yield modeling, and forest ecosystem analysis. We developed tree volume models for two important tree species (*Pinus roxberghii* Sarg. and *Cedrus deodara* Roxb.) in Nepal using data from many individuals (mature trees and juveniles) representing wide variations of tree volume allometry. We used diameter at breast height, total height, and crown width of the individuals as predictors in tree volume models for *Pinus roxberghii* while only the former two predictors in the models for *Cedrus deodara.* All the mathematical functions described more than 91% and 97% tree volume variations for *Cedrus deodara* and *Pinus roxberghii*, respectively. Models for *Pinus roxberghii* revealed almost similar effect of crown width as tree height on tree volume allometry. Models for this species can be applicable for predicting tree volume with and without bark; however, models for *Cedrus deodara* can only predict the over-bark tree volume. Testing *Pinus roxberghii* model against external independent data confirmed a high accuracy of the model. The proposed tree volume models for the species of interest are biologically plausible and statistically robust, and therefore, can be applied to estimate the growing stock precisely, carbon accounting, timber valuation, forest growth and yield modeling. However, users need to apply the model with caution for the forest conditions not covered by modeling data for *Cedrus deodara*. The prediction accuracy of the models can be further improved through recalibration with additional data collected from wider distributions of the species of interest across the Karnali province and beyond, and application of more robust modeling methods, such as mixed-effects modeling and machine leaning.

1. Introduction

Based on the international agreements on the global warming, biodiversity, and sustainable forest management, each country needs to continually report the condition of the growing stocks to the United Nations Framework Convention on Climate Change (UNFCCC) (Cysneiros et al., 2020; McRoberts et al., 2012). Forest inventories of different scales, such as regional or national forest inventories and growing stocks estimation are significant for this. Growing stocks are estimated using the tree-based volume prediction models (Gschwantner et al., 2019). The estimates obtained by tree volume models are aggregated at the sample plot level, and the plot-level estimates are averaged over the plots to produce forest-area estimates, often expressed on a per-unit area basis (McRoberts and Westfall, 2016). Estimate of the growing stock expressed in the form of standing tree volume has been becoming a global interest, especially in the context of the carbon accounting system (Lindner and Karjalainen, 2007; MacFarlane, 2011). The developed tree volume models are fundamental basis for estimating tree biomass and carbon amount with use of wood density and various conversion factors and ratios (IPCC, 2006). Thus, the precise estimates of tree volume are

* Corresponding author.
E-mail addresses: kamalrajaryal@nepal.gov.np, kamalrajaryal2003@gmail.com (K. Raj Aryal).

https://doi.org/10.1016/j.foreco.2023.121364
Received 5 May 2023; Received in revised form 24 July 2023; Accepted 15 August 2023

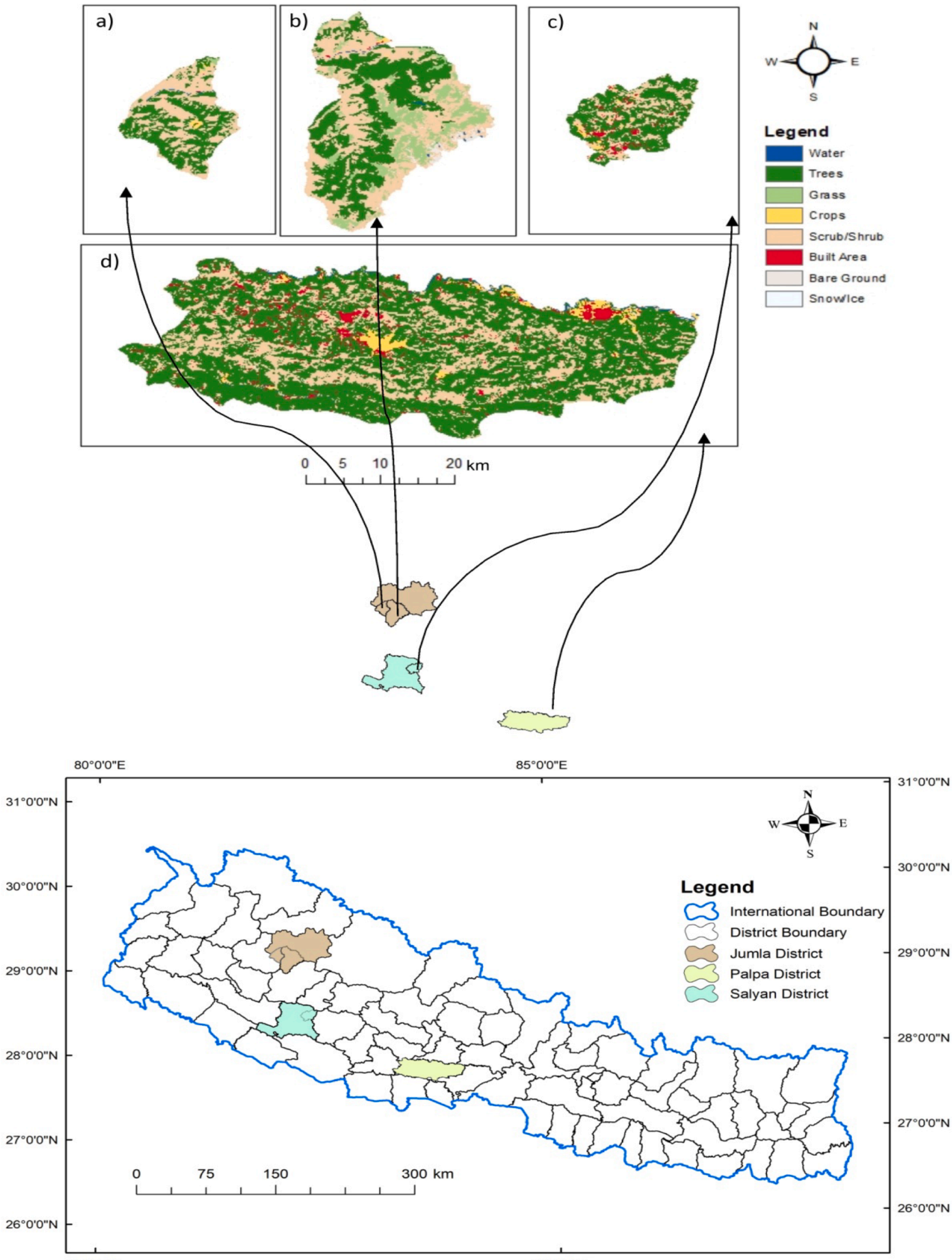


Fig. 1. Location map of study area; Land use land cover map 2020 a) Tila Rural Municipality b) Tatopani Rural Municipality c) Bagchaur Municipality d) Palpa District.

considered important to estimate forest biomass and carbon amount precisely, timber valuation, identifying forests for harvesting, forest growth and yield modeling, forest management, silvicultural research, and forest ecosystem analysis (Clutter et al., 1983; Gschwantner et al., 2019; Kershaw et al., 2017; Kim and Lee, 2016; Mauya et al., 2014; Thangjam et al., 2019). However, direct measurement of tree volume in the field is largely tedious and impractical for the extensive area, as this is a hugely time-consuming, costly, and error-prone approach (Kershaw et al., 2017). Thus, development of the tree-based volume model, which is expressed as a function of some predictor variables, such as tree diameter, height, tree form, and other factors, is used as the best means to predict tree volume of the species of interest. Modeling tree volume represents an acceptably accurate, easy, cheap, and versatile approach (Weiskittel et al., 2011). Data for developing tree volume models usually comes from the destructive sampling and measurements. However, because of data acquisition difficulty (Gimenez et al., 2017) and strict legal restriction imposed to live tree felling, tree volume modeling is rare elsewhere in the world (Cysneiros et al., 2020). Despite this, considerable works on modeling tree volume have already been carried out (Domke et al., 2013; Gschwantner et al., 2019; Kachamba and Eid, 2016; Kershaw et al., 2017; Kim and Lee, 2016; Ko et al., 2019; Lee et al., 2017; Mauya et al., 2014; Planck et al., 2014).

Tree volume is largely affected mainly by tree- and stand-level characteristics, such as tree forms and crown architecture (Forrester et al., 2021; Štícha et al., 2019), stand density or competition, and external factors, such as site quality (Štícha et al., 2019) and environmental factors. Thus, tree volume can be precisely predicted only when the robust modeling method is employed, and all the tree volume influencing factors are included as predictors in the models (Wirth et al., 2004).

Diversified tree species exist in Nepal, covering about 46% of the country (DFRS, 2015; Tiwari et al., 2020). However, only limited studies involving the development of tree volume models are available in Nepal (Baral et al., 2021; Mandal et al., 2020; Sharma and Pukkala, 1990; Shrestha et al., 2018b; Silwal et al., 2018; Subedi, 2018; Thapa et al., 2012; Ulak et al., 2022) and most of these are based on data collected from easily accessible forests, such as low land tropical and sub-tropical species, which are not representative to the forest and trees species in other regions, such as remote parts of the country. Except for tree volume models developed by Thapa et al. (2012) and Sharma and Pukkala (1990), none of the tree volume models is available for *Pinus roxberghii* and *Cedrus deodara* in Nepal. The existing models are based on the non-robust modeling approach and poor-quality data; and therefore their prediction accuracies could not be satisfactory. Some severe issues have been raised on the tree volume models developed by Sharma and Pukkala (1990), such as tree volume was estimated on the measurements of standing trees without destructive sampling. For high accuracy, measurements of destructively sampled trees must be used for volume modeling, which may not be possible in general (Cysneiros et al., 2020; Gimenez et al., 2017). Furthermore, tree models developed by Sharma and Pukkala (1990) do not represent data below 12 cm diameter at breast height (DBH), and the range of which (juvenile stage of forest) is considered very important from the perspective of carbon accounting (Chapagain and Sharma, 2021; Hogg et al., 2021). This is the reason that all the tree volume models developed by Sharma and Pukkala (1990) cannot meet the standard of the UNFCCC reporting requirements and are not appropriate for claiming the emission reduction credits for REDD + results-based payment (Baral et al., 2021).

The government of Nepal has handed over one-third of the total forest area to the thousands of forest user groups under the community forestry program, which is considered one of the highly successful forest management approaches as a result of largely increased forest area and improved livelihood (DFRS, 2015; Tiwari et al., 2020). However, technical aspect of this approach is extremely poor, as no priority is set in the national policy system for scientific studies, such as forest modeling in the context of climate warming. Tree volume estimation is being practiced in Nepal by assuming the form factor of 0.5, which may lead to large biases in the estimated tree volume and biomass, as form factor significantly varies with tree species and tree size, even for the same species and sizes from region to region within the country (Baral et al., 2021; Chapagain et al., 2014). The quarter girth formula recommended by Forest Acts, Nepal is practiced for tree volume estimation, as this has been declined to use elsewhere in other parts of the world because of an increased globalized market of timbers and woods and needs some standard methods of estimating tree volume and biomass (Kershaw et al., 2017). As pointed out earlier, existing tree volume models are based on the data collected from easily accessible forests, and therefore it is necessary to develop tree volume models based on data collected from geographically remote forests, such as the Karnali Province. In addition, all the existing tree volumes models in the country are based either on a single predictor variable (DBH) or two predictor variables (DBH and height). As other tree factors, such as crown dimensions and form factors could largely affect the tree volume allometry (Chapagain and Sharma, 2021; Baral et al., 2021), inclusion of such factors in the models may improve their accuracy.

This study intends to develop the tree volume models for two important tree species: *Pinus roxberghii* and *Cedrus deodara* in two remote districts (Jumla and Salyan) of the Karnali Province, the richest Province of natural resources among seven Provinces of the country. Biophysical and economic contributions of these species are substantial to the country (Jackson, 1994). Developing tree volume models for these species can offer the tools for informed decision-making in forestry in the province. The objective of this study was to develop the best-fit tree volume models using DBH, height and crown width as predictor variables for *Pinus roxberghii* and former two predictors for *Cedrus deodara*. Data from destructive sampling (former species) and non-destructive sampling (latter species) were used for the purpose. We hypothesized that crown dimension used as a covariate predictor would contribute significantly to the model. The proposed models are biologically plausible and statistically robust and can be applied for the precise estimation of growing stock, carbon accounting, timber valuation, forest growth and yield modeling of the species of interest.

2. Materials and methods

2.1. Study area

This study was carried out in the monospecific natural forests of *Pinus roxberghii* and *Cedrus deodara* in two remote districts of Nepal (Salyan and Jumla) in the Karnali Province (Fig. 1). *Pinus roxberghii* forest is located between 1200 and 1400 m from asl in the southern aspect of Bagchaur municipality of Salyan district. The mean annual maximum and mean annual minimum temperature is 25.5° C and 13.4° C, respectively, and the mean total annual precipitation is 1162.9 mm (DHM, 2017). *Cedrus deodara* forest is located in the elevation between 2200 m and 2800 m of Tatopani and Tila rural municipalities of Jumla district. The mean annual maximum and mean annual minimum temperature is 13° C and 1.3° C, respectively, and the mean total annual precipitation is 861.4 mm (DHM, 2017). Both forest types represent wide variations of site quality, stand density, age structures, and stand development stages. Considering the unique characteristics of the forests of the species of interest (remotely located, diversified tree growth conditions, etc.), these sites were selected.

2.2. Sampling and measurement

We collected data using both the destructive and non-destructive samplings with the former method applied to *Pinus roxberghii* and juvenile *cedrus deodara*, and the latter method to mature *Cedrus deodara* only. Descriptions of sampling and measurement are pesented below.

Pinus roxberghii: a total of 110 mature trees (well-established individuals with DBH $\geq$ 10 cm) and 40 juveniles (DBH $<$ 10 cm) were

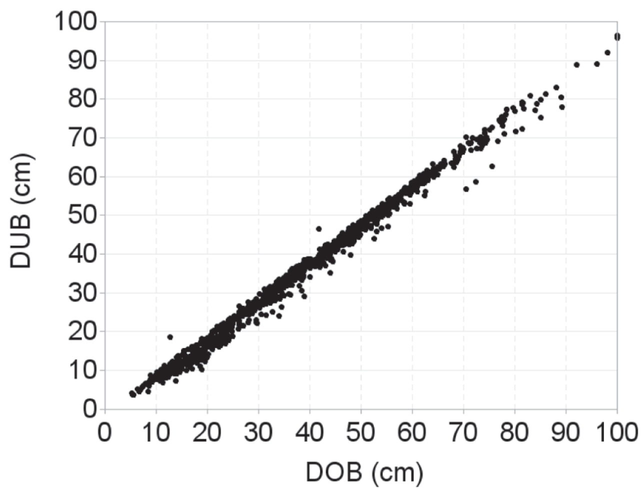


Fig. 2. Relationship between under bark diameter (DUB) and over bark diameter (DOB) of *Pinus roxberghii*.

selected for felling and measurement from March through June 2022. We selected sample trees based on subjective criteria (convenience sampling), such as the representativeness of all the size classes and tree quality classes in the tree population of interest. Only healthy, undamaged, and live trees were selected for felling. For mature trees, diameters at 0.3 m, 0.8 m, and 1.3 m (DBH over bark) from the base of the tree were measured. Total tree height, crown length, and crown width were also measured before felling. In order to make cylindrical shape of the stem section considered, this should be as short as possible (Kershaw et al., 2017). Crown width was measured in two perpendicular directions from the location of each tree (N-S and E-W), and an average of two values was considered a real crown width value. Sample trees were felled and divided into a number of sections, and measured the diameters at 1.5 m intervals along the stem up to the clear tip. The number of measurements along the stem varied up to 25 depending on length of stem up to 10 cm of the top diameter for mature trees and 5 cm for juveniles. The stem ending (near to the tip) below 0.75 m interval from the consecutive point was disregarded, while above 0.75 m was considered as a 1.5 m interval.

Cedrus deodara: a total of 161 mature trees and 36 juveniles (considered the exact definition as in *Pinus roxberghii*) were identified for measurement. We measured DBH (over bark) and total height for both mature and juvenile individuals. Destructive sampling was not considered for *Cedrus deodara* mature trees because of resource constraints. Instead, we used the Dendrometer Criterion RD 1000 (Lasertech 2019), which measures the upper diameter more accurately than any other conventional instrument, to measure the upper diameters above the breast height (1.3 m) along the stem (Biazatti et al. 2020). The number of measurements varied up to 31 depending on length of stem up to 10 cm of the top diameter for mature trees and 5 cm for juveniles. We measured the cross-section diameter from four different directions (N-E-S-W) and considered the average value as true diameter at the measurement point. Diameters at 0.3 m, 0.8 m, and 1.3 m from the base of the tree were measured using Diameter tape. For juveniles to be felled, we measured the diameter at stem cross-section (over bark) at an interval of 1 m starting from 0.3 m from the base. After felling, diameters at stem cross-section were measured at an interval of 1 m from DBH up to 5 cm of the top diameter. The section of stem ending (near to the tip) at lower than 0.5 m lengths from the consecutive point of the stem was disregarded, while longer than 0.5 m section from the consecutive point of the stem was considered as 1 m interval.

2.3. Predicting under-bark diameter

We measured both the under-bark and over-bark diameters for most of the mature sample *Pinus roxberghii* trees, but not the under-bark diameters for all the juveniles of this species. Under bark, diameters were not measured for both the trees and juveniles *Cedrus deodara*. There were still a total of 112 bark observations missing for some mature *Pinus roxberghii* trees, and all the under bark diameter observations were missing for juveniles. All the missing under-bark diameters (DUBi) were predicted using a linear regression model developed with the expression of under-bark diameter as a function of over-bark diameter (DOBi), as they were strongly linearly correlated with each other (Fig. 2).

Mathematically, Eq. (1) represents such a linear regression.

$$DUB_i = b_1 + b_2 DOB_i + \varepsilon_i \tag{1}$$

where b1 and b2 are parameters to be estimated and ε_i is error term, which is assumed to have normal distribution with mean zero and variance one. The estimated values of b_1 and b_2 are −2.59744 and 0.988635, respectively, and the coefficient of determination (R^2) of this model is 0.9929.

2.4. Computing tree volume

The total volume of stem for each sample tree was calculated using the following expression (Eq. 2):

$$v_i = \pi \frac{\left(\frac{d_{1i}+d_{2i}+d_{3i}+d_{4i}+\cdots+d_{ni-1}+d_{ni}}{ni}\right)^2}{4} l_i \tag{2}$$

where v_i is tree volume for tree i, d1i, d2i, ……dni is diameter measurements at n number of points along the stem, l_i is total length of stem measured at 0.3 m above ground to the top, and it was obtained by summing up of the length of all the sections assumed in stem profiling; and πis constant, whose value is 3.1416. The relationships between tree volume determined by Eq. (2) and diameter at breast height (over bark), total height, and crown width are shown in Fig. 3, and all the measured variables and estimated variables, including tree form factors, are summarized in Table 1.

2.5. Model validation data

The validation data set was acquired from the geographically distant location (Palpa district of Lumbini Province (Fig. 1 d), as such data set was not available in the Karnali province. This data set was collected by the government forest office from recently felled trees according to yearly felling plan. Three *Pinus roxbeghii* dominated natural stands managed by local community as community forest (CF), and they are Rampokhari CF, Pakhure CF and Nayadevi CF. The elevation of forests ranges from 960 m to 1606 m from asl. The mean annual maximum and mean annual minimum temperatures of the area are 26.1° C, and 14.8° C, respectively, and mean total annual rainfall is 1680.5 mm (DHM, 2017). Other tree species associated with *Pinus roxberghii* are *Schima wallichii*, *Shorea robusta*, *Rhodendron* species and *Castanopsis* species. The forests cover a wide range of tree size and allometry, stand density, stand age, site quality, and crown architectures. To account for different stand developmental stages, a stratified random sampling was applied to lay out 31 sample plots of 400 m^2 (20 m × 20 m). DBH of all the trees greater than 5 cm of DBH in the sample plot were recorded, and then 1 to 4 trees (healthy and undamaged tree with different size characteristics) per sample plot were selected for harvesting. We obtained data from 80 trees that were felled. Before felling, diameters along the stem were measured at 0.3 m, 0.8 m, 1.3 m above ground. After felling, diameters were measured at every 1.5 m along its length above 1.3 m above ground. Diameters were measured immediately above the branches or other irregularities that were present at the specified point of measurements. Felling and measurements were carried out on March through June

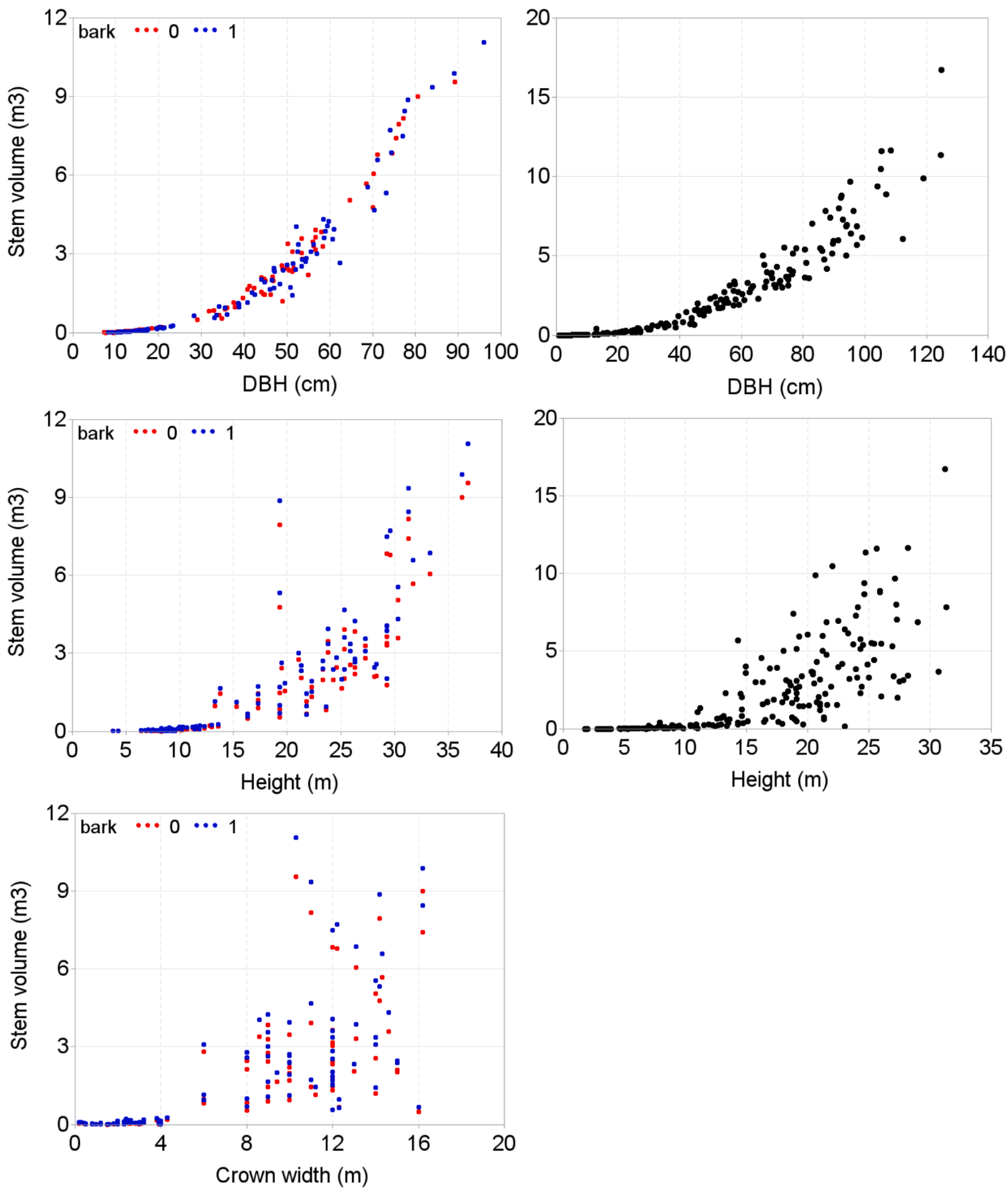


Fig. 3. Tree volume plotted against diameter at breast height (over bark) and total height. Left panel is for *Pinus roxberghii* and right panel for *Cedrus deodara*. Bark 0: tree volume without bark; bark 1:tree volume with bark.

2022. The average stand density and mean DBH of forests were 525 trees ha^{-1} and 19.94 cm, respectively. Summary statistics of the measured tree variables in the validation data are presented in Table 2. Total over-bark tree volume of each harvested tree was obtained from the sum of stem section volumes. Stem section volumes were estimated using the prismoidal formula (Newton formula), which would provide the most accurate volume of any frustum shape (Kershaw et al., 2017).

2.6. Model development

We started modeling works with examination of graphic patterns of the tree volume plotted against DBH (Fig. 3) and chose those mathematical functions which could describe such patterns adequately. As DBH exhibited the strongest nonlinear relationships with tree volume (Fig. 3) and described most part of the tree volume variations of the species of interest, we used this as a main predictor. We chose only the versatile nonlinear functions including power and exponential functions (Table 3), to fit data. For *Pinus roxberghii*, a dummy variable modeling approach was applied to differentiate the tree volume variations caused by bark thickness. This allows a single model applicable to estiamtion of both the over-bark and under-bark volumes. We examined the standardized residuals of the models to know whether there existed the heteroscadesticity problems. However, we did not find a serious problem that could cause bias. This gave the impression that application of any variance stabilizing methods (e.g., weighted regression, variables transformation, etc.) was not necessary while estimating models.

Table 1
Summary statistics of tree variables of model fitting data. A number of observations used in the analysis is 1570 for *Pinus roxberghii* and 2024 for *Cedrus deodara*.

Species	Tree variables	Mean	Standard deviation	Minimum	Maximum
Pinus roxberghii	DBH (over bark), cm	40.55	24.75	2.0	96.0
	DBH (under bark), cm	37.51	24.29	0.2	89.1
	Height, m	18.78	9.46	2.3	36.6
	Crown width, m	7.91	5.1	0.2	16.2
	Crown length, m	6.95	3.71	0.4	15.2
	Diameter over bark (DOB), cm	30.81	21.05	0.9	100.0
	Diameter under bark (DUB), cm	27.78	20.94	0.1	96.4
	Over bark tree volume, m3	2.45	2.81	0.0009	11.1
	Under bark tree volume, m3	2.13	2.49	0.0002	9.56
	Form factor (over bark)	0.60	0.09	0.41	0.97
	Form factor (under bark)	0.55	0.12	0.13	0.98
Cedrus deodara	DBH (over bark), cm	57.86	30.41	0.9	124.9
	Height, m	18.82	6.74	1.8	31.3
	Diameter over bark (DOB), cm	44.06	27.47	0.8	136.4
	Over bark tree volume, m3	3.28	3.11	0.0002	16.71
	Form factor (over bark)	0.60	0.13	0.38	0.98

Table 2
Summary statistics of the destructively sample tree data used for model validation. DBH: diameter at breast height; N: number of sample trees.

DBH class (cm)	N	DBH (cm)	Total height (m)
		Mean ± Standard deviation (Minimum, Maximum)	
0–10	10	7.30 ± 1.48 (5.60, 9.50)	4.19 ± 0.87 (3.10, 5.30)
10–20	14	16.08 ± 2.60 (11.90,19.40)	9.66 ± 3.00 (4.20, 14.60)
20–30	8	24.78 ± 2.73 (20.50,28.20)	16.39 ± 3.40 (10.90, 19.80)
30–40	17	36.38 ± 2.17 (31.80,39.50)	19.24 ± 2.61 (12.50, 23.20)
40–50	22	44.63 ± 2.87 (40.10,49.60)	22.60 ± 2.42 (17.30, 27.10)
50–60	5	51.80 ± 0.64 (50.80,52.50)	24.16 ± 2.97 (20.70, 27.10)
60–70	2	68.75 ± 0.49 (68.40,69.10)	31.70 ± 1.13 (30.90, 32.50)
70–80	2	75.35 ± 5.44 (71.50,79.20)	31.05 ± 0.92 (30.40, 31.70)
Overall	80	33.05 ± 16.94 (5.6, 79.2)	17.24 ± 7.74 (3.10, 32.5)

Table 3
Mathematical functions considered to fit data.

Designation	Function form	Reference
M1	$v_i = b_1 DBH_i^{b_2} + \varepsilon_i$	(Huxley and Teissier, 1936)
M2	$v_i = \dfrac{DBH_i^2}{b_1 + b_2 DBH_i} + \varepsilon_i$	(Hosoda and Iehara, 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 or under bark tree volume of *Pinus roxberghii* tree i or *Cedrus deodara* tree i, DBH_i is the 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.

An asymptotic parameter b_1 of each function in Table 2 was expressed as a function of additional variables, such as height for *Cedrus deodara* (Eq. 3) and height, crown width, and dummy variable (named bark) for *Pinus roxberghii* (Eq. 4).

$$b_1 = \beta_1 H_i^{\beta_2} \tag{3}$$

$$b_1 = \beta_1 H_i^{\beta_2} + \beta_3 CW_i + \beta_4 bark_i \tag{4}$$

where H_i and CW_i are the total height and crown width of tree i, respectively; b_1, β_1, β_2,……, β_4 are parameters to be estimated. Here, bark is a dummy variable, which takes 1 for over-bark tree volume estimation and 0 for under-bark tree volume estimation for *Pinus roxberghii*. Dummy variable accounts for variations caused by bark thickness, which varies from stem base along up to the top.

2.7. Model estimation and evaluation

We estimated models using the PROC MODEL in SAS (SAS Institute Inc., 2016) through the application of the Marquardt's method (Marquardt, 1963). We used five statistical indices: root mean square error (RMSE) (Eq. 5) adjusted coefficient of determination (R^2adj) (Eq. 6), Mean residuals (MR) or mean prediction error (MPE) (Eq. 7), precition bias (Eq. 8), and Akaike information critrrion (AIC) (Eq. 9) to evaluate the fitting/ prediction performance of models. The first index analyzes the precision of estimation and second index reflects total variability described by model by considering a total number of parameters to be estimated, third and fourth index provide the mean residuals or mean prediction errors, and fifth index is based on minimizing the Kull-back-Lieber distance, which imposes a penalty for number of parameters included into the model. All these indices are expressed as below (Akaike, 1972; Burnham and Anderson, 2002; Montgomery et al., 2012). The third and fourth indices (Eq. 7, 8) are specifically used for evaluation of models using validation data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (v_i - \widehat{v}_i)^2}{n - p}} \tag{5}$$

$$R^2_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \; with \; R^2 = \frac{\sum_{i=1}^{n} (v_i - \widehat{v}_i)^2}{\sum_{i=1}^{n} (v_i - \overline{v})^2} \tag{6}$$

$$MPE = \frac{\sum_{i=1}^{n} (v_i - \widehat{v}_i)}{n} \tag{7}$$

$$Bias\% = \frac{MPE}{\overline{v}} \times 100 \tag{8}$$

$$AIC = f(\beta) + 2p \tag{9}$$

where n is total observations; v_i and $\widehat{v}_i$ are observed and predicted tree volumes; $\overline{v}_i$ is the average value of the observed volume; $i = 1, 2, \ldots, n$; p is the number of parameters of the model; f (β) is negative of the marginal log-likelihood function; and β is vector of parameters.

In addition to these indices (Eq. 5–9), residual graphs and the volume curves produced with each model were also examined, which would help readers to understand whether models would be featured with the theoretical basis and biological logic (Zeide, 1993). Unless otherwise specified, we used 1% level of significance in our analyses. Validation of the models is one of the important procedures of modelling, as this provides more credibility and confidence about models. We only validated our model for *Pinus roxberghii*, but not for *Cedrus deodara* due to a lack of funding to collect new data. We did not validate our models through data splitting, because this does not make much sense, as both

Table 4
Parameter estimates and their p-values, and fit statistics of four models fitted to data. RMSE: root mean square errors (Eq. 5); R^2_{adj}: adjeusted coefficient of determination (Eq. 6); MPE: mean residuals or mean prediction errors (Eq. 7); AIC: Akaike information criterion (Eq. 9). All other symbols are as defined in the text.

Species	Model	Parameter estimates and p-values					Fit statistics			
		β_1	β_2	β_3	β_4	b_2	RMSE	MPE	R^2_{adj}	AIC
Pinus roxberghii	M1	0.000149 (<0.0001)	0.094438 (<0.0001)	0.0000052 (<0.0001)	−0.00001 (<0.0001)	2.352784 (<0.0001)	0.4400	0.1868	0.9735	−5151
	M2	1527.747 (<0.0001)	−0.03878 (<0.0001)	−17.074 (<0.0001)	25.07225 (<0.0001)	−4.07096 (<0.0001)	0.4625	0.2007	0.9707	−4929
	M3	24.61692 (<0.0001)	0.177075 (<0.0001)	0.715493 (<0.0001)	−0.54242 (<0.0001)	151.6793 (<0.0001)	0.4291	0.1773	0.9748	−5311
	M4	294.1312 (<0.0001)	0.129357 (<0.0001)	8.799858 (<0.0001)	−9.72802 (<0.0001)	37.99285 (<0.0001)	0.4183	0.1711	0.9760	−5419
Cedrus deodara	M1	0.000134 (<0.0001)	0.58296 (<0.0001)			1.984319 (<0.0001)	0.7731	0.5977	0.9302	−1028
	M2	100.7562 (<0.0001)	−0.39724 (<0.0001)			−0.1533 (<0.0001)	0.8435	0.7115	0.9170	−999
	M3	7.250459 (<0.0001)	0.527001 (<0.0001)			158.4013 (<0.0001)	0.8088	0.6541	0.9237	−847
	M4	49.4599 (<0.0001)	0.545719 (<0.0001)			35.62194 (<0.0001)	0.7786	0.6062	0.9292	−677

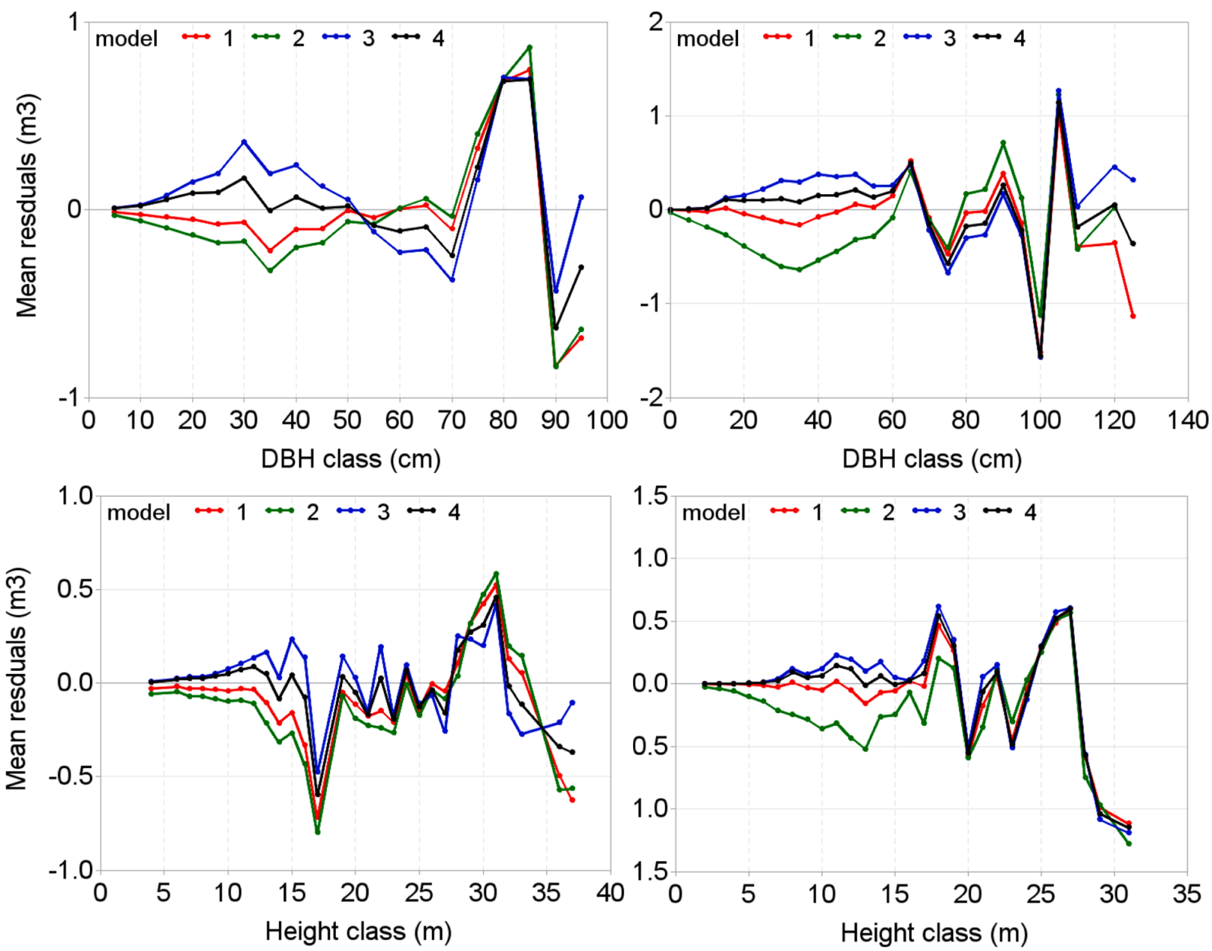


Fig. 4. Each model's mean residuals were calculated by DBH class and height class with 5 cm and 1 m intervals, respectively. Left panel for *Pinus roxberghii* and right panel for *Cedrus deodara*, DBH: diameter at breast height (over bark).

fitting and validation data sets do have similar statistical characteristics (Chapagain and Sharma, 2021; Hirsch, 1991; Kozak and Kozak, 2003; Yang et al., 2004; Zhang, 1997). Only validating model with external independent data can be the best alternative (Crecente-Campo et al., 2010; Sharma et al., 2011).

We compared our tree volume models against those developed in Nepalese and Indian contexts (Chaturvedi and Khanna, 2011; Sharma and Pukkala, 1990). As potential growth conditions for the species of interest are more or less similar in both countries, it could reasonable to compare tree models originating from these countries (Baral et al., 2021).

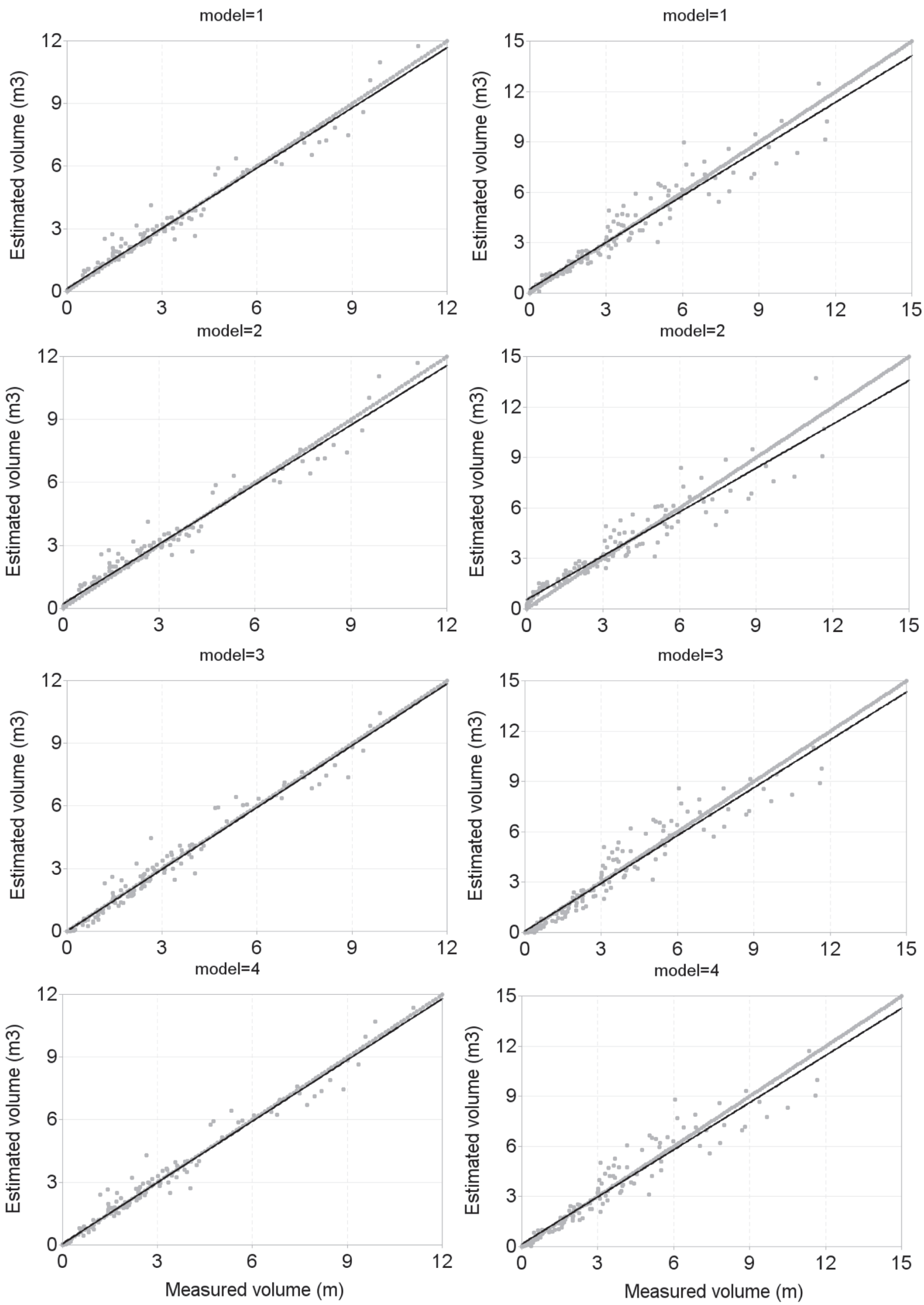


Fig. 5. Data overlaid on the straight line (1:1 line, dotted line) and regression line (black line) produced from the predicted tree volume regressed against the measured tree volume. The left panel (column) is for *Pinus roxberghii*, and the right panel (column) is for *Cedrus deodara*.

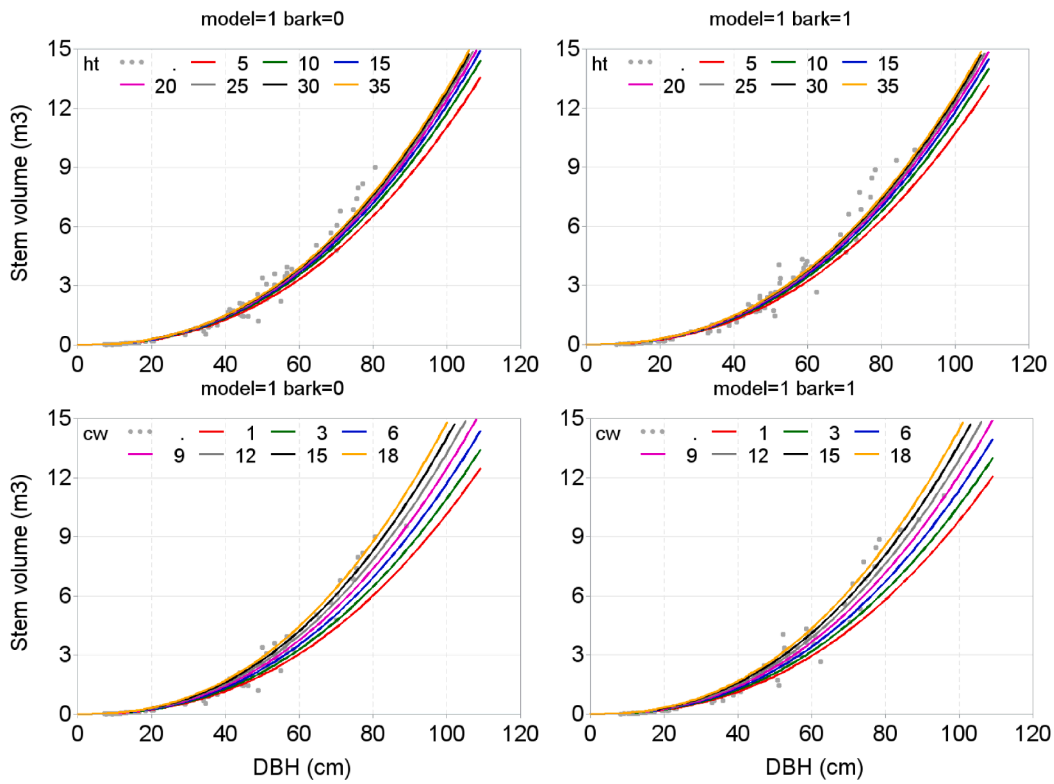


Fig. 6a. Model curves overlaid on the measured tree volume data for *Pinus roxberghii*. Mean values of the data were used for covariate predictor of the model, except the variable of interest in the figure that was allowed to vary from about minimum to maximum values in the measured data. Acronym cw stands for tree crown width (m) and ht for total tree height (m) of *Pinus roxberghii*, and DBH stands for diameter at breast height (over bark).

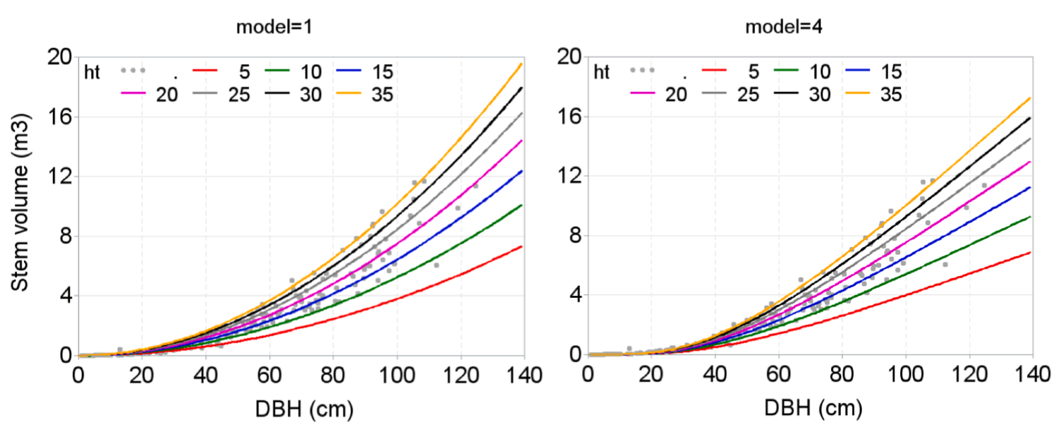


Fig. 6b. Model curves overlaid on the measured tree volume data for *Cedrus deodara*. With the variation of predictor variable ht of tree from about minimum to maximum values in the measured data, tree volume significantly varied.

3. Results

All the parameter estimates of each model for both species were highly significant ($p < 0.0001$), and all the models were able to describe the tree volume variations by 97% for *Pinus roxberghii* and 91% − 93% for *Cedrus deodara* (Table 4). Stastitical indices showed that models better fitted to *Pinus roxberghii* data than *Cedrus deodara* data, as one more predictor is present in the models of the fomer species. Among four functions fitted to data, M4 for *Pinus roxberghii* and M1 for *Cedrus deodara* described the largest portion of the tree volume variations. The smallest AIC and smallest MPE were provided by M4 and M1 for *Pinus roxberghii* and *Cedrus deodara,* respectively.

We produced the mean residuals for each model (Fig. 4). Compared to other models, M3 and M4 for *Pinus roxberghii* and M1 and M4 for *Cedrus deodara* showed smaller residual variations within a range of the majority of observations (30–65 cm DBH and 15–30 m for *Pinus roxberghii*, and 40–100 cm DBH and 15–30 m for *Cedrus deodara*. The raw residuals also followed the normal distributions.

From a closer look at the residual variations (Fig. 4), M1, M3, and M4 for *Pinus roxberghii* and M1 and M4 for *Cedrus deodara* were considered for further analyses, such as analysis of graphs of the model-estimated volume and measured volume (Fig. 5). Model passing through data clouds and regression line closer to the 1:1 line could be considered as a better performing model. It seems that M1, M3, and M4 for *Pinus roxberghii* and M1 and M4 for *Cedrus deodara* appeared closer to each other, and therefore it needed further analysis, which was an examination of

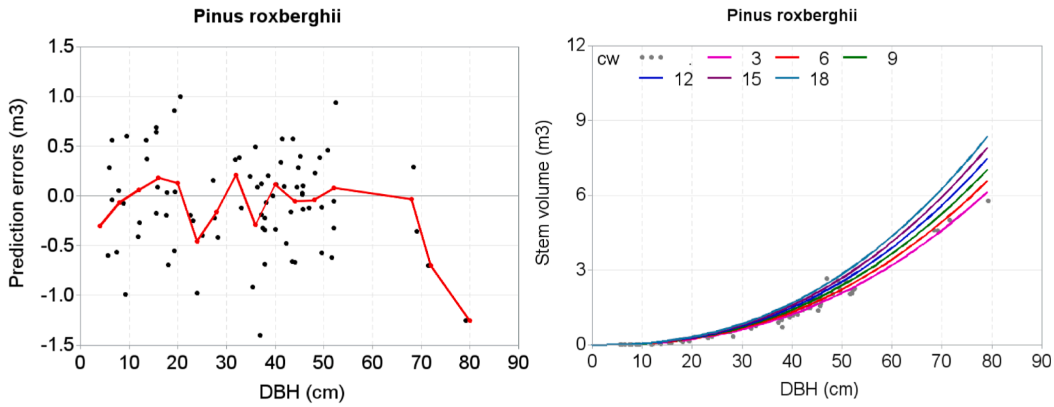


Fig. 7. Test results of tree volume model (M1) against independent data of *Pinus roxberghii*. The prediction errors of M1 applied to test data for which mean rediction error shown as a red line was calculated by DBH class with 5 cm interval (left). Model curves overlay on test data (right), DBH: diameter at breast height and CW: crown width. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the model curves overlaid on the measured volume data.

We examined the tree volume curves produced with each model and overlaid them on the measured tree volume data (Annex-1). M1 for *Pinus roxberghii* and M4 for *Cedrus deodara* appeared biologically more plausible than other competing models including M3, which shows more appealing appearance in Fig. 5. For the brevity of space, we have only presented the model with the most appropriate volume curves (Fig. 6a (*Pinus roxberghii*), Fig. 6b (*Cedrus deodara*)). These figures show magnitudes of the effects of height and crown width on the variations of tree volume allometry.

Model (M1) described the independent external data adequately well (MPE = 0.1177; Bias = 9.15%; $R^2 = 0.90746$) without serious systematic trends in the errors within a range of the majority of test data (Fig. 7).

4. Discussion

Tree volume models are fundamental tools for estimating timber volume, growing stock, forest biomass, and carbon assessment. Therefore, accurate estimate of tree volume is necessary, which is possible only with the tree volume models developed using comprehensive data set and robust modeling approach (Chapagain and Sharma, 2021). We developed the tree volume models for individual trees growing in the natural forests of *Pinus roxberghii* and *Cedrus deodara* in Salyan and Jumla Districts- remotely located districts of Nepal, respectively (Fig. 1). Our data sets represent a wide range of mature tree and juvenile sizes, covering all the potential variabilities of the variables of interest (Table 1 and 2, Fig. 3), which is the main basis for developing robust models. Chosen candidate functions (Table 3), which are flexible enough to describe a wide range of the variations of a response variable of interest (tree volume, in our case), have frequently been used by many other modelers to develop forest models (Hosoda and Iehara, 2010; Huxley and Teissier, 1936; Schumacher, 1939; Sharma et al., 2016; Shrestha et al., 2018a). A decision to use the correct form of candidate functions to fit data is the most important step in developing robust model, which should be in accordance with data patterns. Nonlinear functions effectively described data patterns (Fig. 3) effectively without serious residual trends (Fig. 4).

Models describe most of the variations of tree volume allometry (Table 3), confirming that selected functions (Table 2) are suitable to our data and flexible enough to cover all the variations of tree volume allometry. Compared to models for *Cedrus deodara*, *Pinus roxberghii* models show better fit statistics (Table 4) and more appealing graphical appearance (Fig. 5, 6). It may be due to fewer observations and their narrower variations of tree volumes for *Pinus roxberghii* (Fig. 3). When there would be low variations covered by data (highly concerntrated data distribution), models could show better fit statistics (Shrestha et al., 2018a). Non-existence of systematic trends in the residuals (Fig. 4) confirms the model's adequacy and precision. A clear differentiation of the curves produced with final model within a range of the measured data, even for the same DBH, is due to the significant effects of other covariate predictors (Fig. 6). Because of different heights and crown dimensions of the sampled trees used in modeling, predicted volumes are expected to be significantly different, even for the same DBH as shown in Fig. 6. This figure shows there is an dequate coverage of the model curves to the varations of measured volumes of mature trees and juvenile individuals. This suggests that our developed models are biologically plausible, theoretically robust, and statistically flexible. Smaller residual variations for smaller individuals (Fig. 4) suggest that our models can be more accurate for small trees and juveniles than larger trees. This may be due to fewer observations from larger trees used in model fitting compared to smaller individuals.

The modelers prefer using DBH as a single predictor in the tree volume models to make resulting models simpler, as this could often describe most of the variations in tree volumes. For example, our models fitted with DBH only described 89–90% variations in the volumes for *Pinus roxberghii* and 87–88% for *Cedrus deodara.* Similarly, models with both DBH and tree height described 94–95% variations for the former species and 92–93% for the latter species. The models with DBH as a single predictor would have a limited application, as they could provide biased prediction in the situation where trees of similar DBH may have significantly different heights. This commonly exists in any forest stand, even if a stand is too small. Thus, adding tree height as a covariate predictor could significantly improve the model's precision, but not so much (partial-R^2 is about 5%) as DBH and tree height are related with each other (Lee et al., 2017). Inclusion of other tree factors, such as HDR (a measure of tree slenderness) and crown dimension (a measure of tree vigor and health) into the tree volume models, may increase the accuracy, and accordingly models would have a wider scope of application. Considering this, we added total height as a covariate to the *Cedrus deodara* models and tree height and crown width as covariates to the *Pinus roxberghii* models, and due to this, fitting improvement significantly improved, confirming an existence of significant influence of crown width and tree height on the variations of tree volume allometry (Fig. 6).

Our model exhibits the increased volume with increasing total height and crown width (Fig. 6), which is biologically plausible. It seems that there is a more pronounced effect of crown than height on the variations of tree volume allometry for *Pinus roxberghii* despite its lower contribution to the model (its partial-R^2 is smaller than height). Tree crown significantly affects tree biomass, form factor, and tree volume (Baral et al., 2021; Bishowkarma et al., 2019; Chapagain and Sharma, 2021). A tree crown is a mass of foliage characterized by crown length, crown

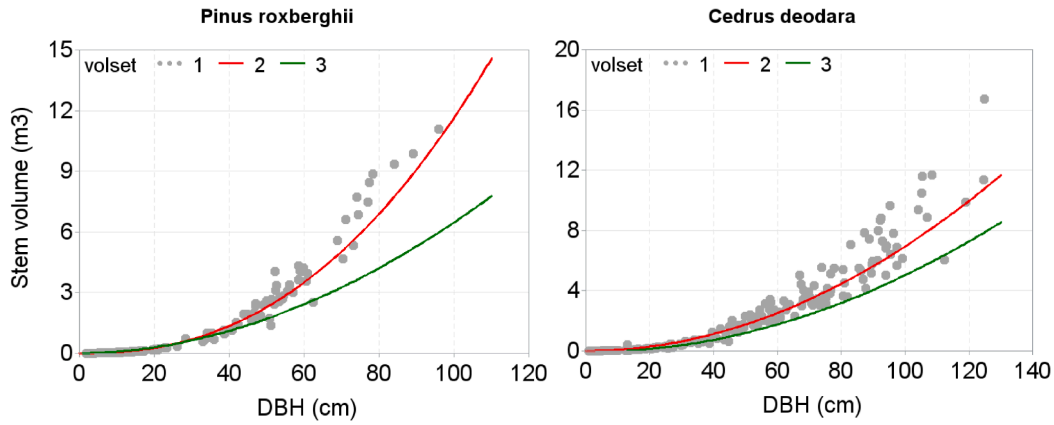


Fig. 8. Volume models developed in the current study (volset = 2, M1) and volume models developed in the previous studies (volset = 3). Dots (volset = 1) are measured tree volume data in the current study. Pinus roxberghii tree volume model by Sharma and Pukkala (1990) and Cedrus deodara tree volume model by Chaturbedi and Khanna (2011) were used for comparison. The comparison involves using average tree volume (over bark) with mean height and mean crown width values to generate mean volume curves. DBH is over bark diameter at breast height.

width, crown density, leaf area, and crown ratio. Tree crown is a major site for food production from where food is transported to other parts of a tree. Therefore, tree volume and tree biomass are strongly correlated to tree crown (Bishowkarma et al., 2019; Sharma et al., 2018). Tree crowns play important roles in regulating energy, nutrients, water, and therefore they are reflective of general tree health and vigor, such as large and dense crowns are associated with vigorous growth, while trees with small and sparse crowns may have little or restricted growth (Assmann, 1970; Buckley et al., 2013; Sharma et al., 2018; Zarnoch et al., 2004).

Model validation confirms the certainty and confidence of our volume model for *Pinus roxberghii* (Fig. 7). However, lack of independent data on *Cedrus deodara* compelled us not to consider model validation for this species. Validating models through data splitting, which we did not do either, is not a robust idea, as both the fitting and validation data sets would have similar statistical characteristics (Chapagain and Sharma, 2021; Hirsch, 1991; Kozak and Kozak, 2003; Yang et al., 2004; Zhang, 1997). Because both data sets come from the same tree population and the same sampling strategies employed. To make the modeling methods statistically more robust, modelers should use a full data set to estimate model parameters,which helps produce more stable parameter estimates and smaller standard errors.

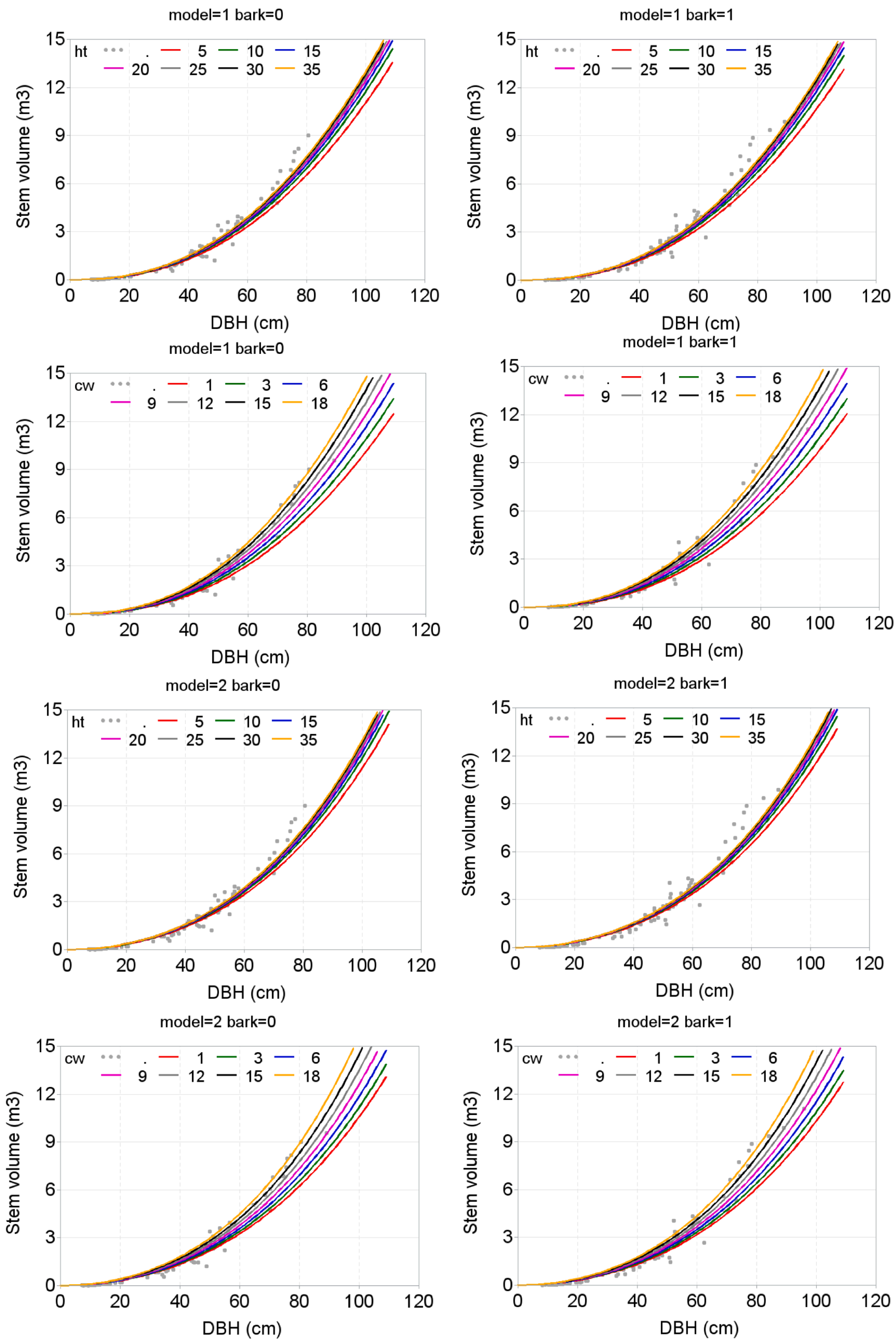
In contrast to this, when validation is done by splitting the data set into 1/3, 1/2,1/4 sets or k-folds (k = 5, 10, 15, 20….n), fitting data set would be significantly smaller than a full data set, and validation errors for the model built on such a smaller data set tends to over-estimate the unknown errors (Chapagain and Sharma, 2021; Hirsch, 1991; Kozak and Kozak, 2003; Yang et al., 2004; Zhang, 1997). Thus, the best alternative is to validate models using the external independent data set (Crecente-Campo et al., 2010; Sharma et al., 2019; Sharma et al., 2011).

As modeling approaches employed in the different forest modeling studies are largely different, the number of predictor variables used in the models are also different, amount of data or the number of observations used in modeling are different, and so on, comparing previously developed forestry models against our models would not be the best approach. However, it might be of interest to the readers if compared our models against the previously developed ones. A comparision of our *Pinus roxberghii* model against the model developed by Sharma and Pukkala (1990), which is based on diameter measurements without destructive sampling, cannot confirm the accuracy their model (Fig. 8). Similarly, a comparison of our *Cedrus deodara* model against the model developed in the Indian condition (Chaturvedi and Khanna, 2011) does not show close relationships of tree volumes from both countries. Other studies (e.g., Baral et al., 2021) have also provided some useful information from the comparisions of the tree volumes models from both countries. There are sytematic underestimation problems of the models developed by Chaturvedi and Khanna, 2011; Sharma and Pukkala, 1990) when they were applied to our data. This analysis also confirms the necessity of developing new species-specific tree volume models based on data sets covering the local geographical setting (or local forests).

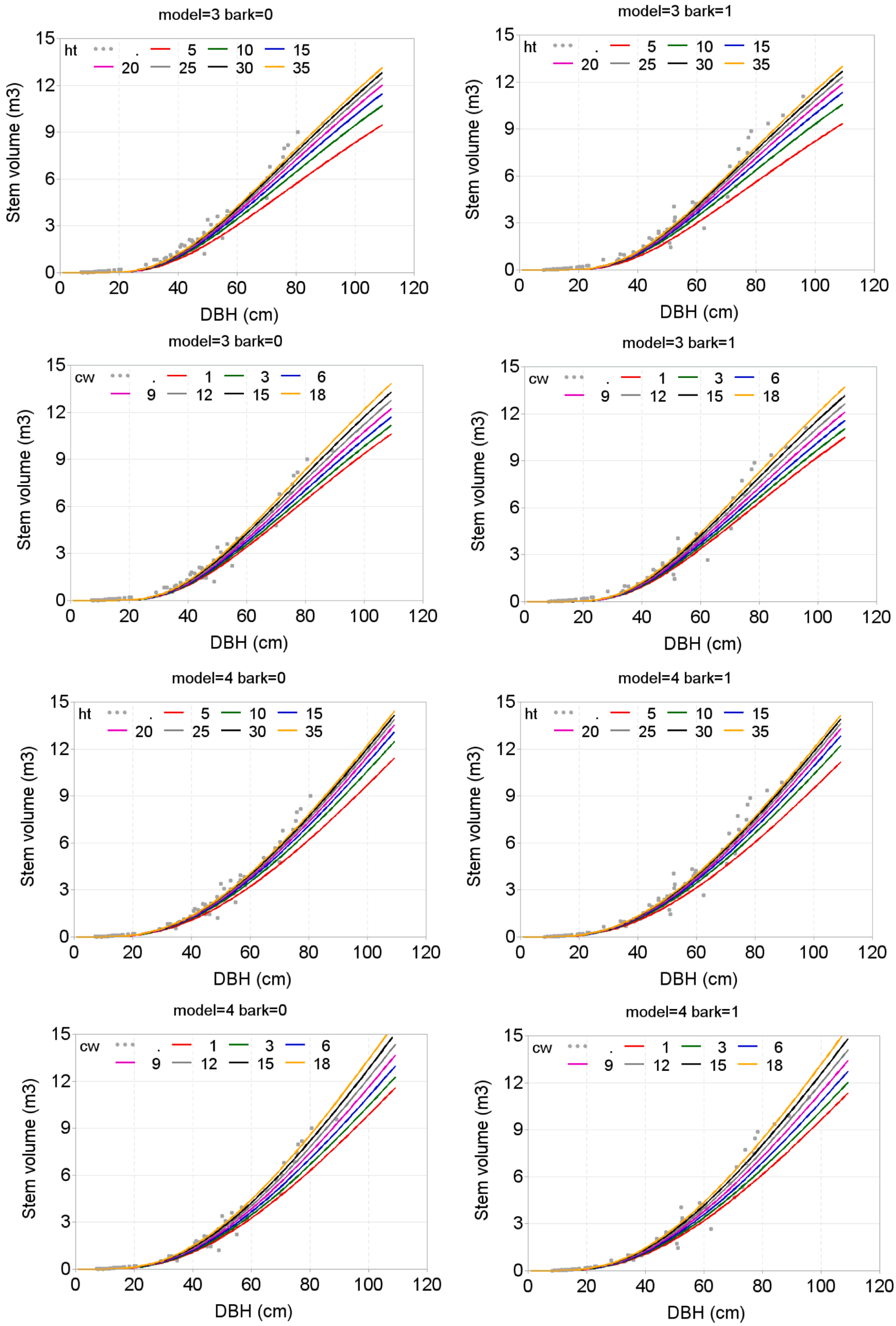
Tree volume is significantly affected by other factors not included in our models, such as environmental factors (site quality, topography, climate) and stand factors (stand development stage, stand structure, competition stress), their inclusion into the tree volume models may increase both the model accuracy and scope of application even though the model becomes more complex. Altrantively, mixed-efefcts modeling can be applied to account for the variabilities caused by these factors, which increases the model acuarcy (Pinheiro and Bates, 2000). Even though our models have robust biological logics (Fig. 6,7) and statistical stability (smaller standard errors, Table 3), it is necessary to validate the model of *Cedrus deodara*. However, it may not be a problem to apply volume model for *Pinus roxberghii* elsewhere across the country, as this model has adequately described the data acquired beyond the Karnali province (Fig. 7). Modeling data used in our study came from small forest area (Fig. 1) where growth variability caused by several factors may not vary as they usually do for a large area. Because of this, our model, especially for *Cedrus deodara*, can be applied to similar forests as a basis of this study and warrant the rigorous testing before applying to other forests, even within the Karnali province. While applying volume models for *Pinus roxberghii,* one should treat dummy variable as defined in Eq. (4).

5. Conclusion

Allometric tree volume models for two important tree species in the Karnali province, a remote part of Nepal, were developed using data collated from a fairly large number of individuals (mature trees and juveniles) representing to sufficiently large variations of the tree volume allometry. Diameter at breast height, total height, and crown width were used as predictors for the *Pinus roxberghii* models, while only former two predictors were used for the *Cedrus deodara* models. All the models described more than 92% variations of the tree volume allometry with better fit statistics obtained for *Pinus roxberghii.* Model validation with an independent external data set confirmed a high accuracy of the *Pinus roxberghii* model. Almost similar effect of tree crown as height existed for *Pinus roxberghii.* The model for this species can be applicable for predicting tree volume with bark and without bark; however, the model for *Cedrus deodara* can only predict over-bark tree volume. The proposed volume model (M1: power model) is biologically plausible, theoretically

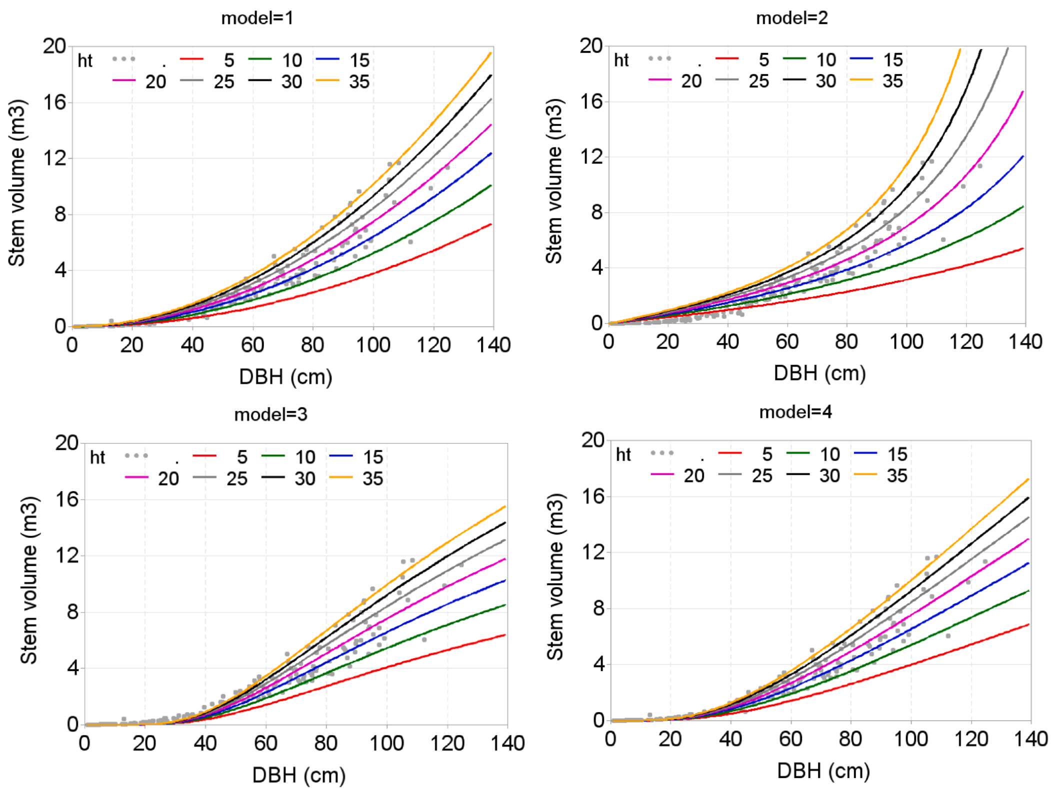


Annex 1a. Model curves overlaid on the measured tree volume data for *Pinus roxberghii*. Mean values of the data were used for covariate predictor of the model, except the variable of interest in the figure that was allowed to vary from about minimum to maximum values in the measured data. Acronym *cw* stands for tree crown width (m) and *ht* for total tree height (m) of *Pinus roxberghii*, and DBH stands for diameter at breast height (over bark).



Annex 1a. (*continued*).

robust, and statistically flexible and can be useful for growing stock estiamtion, carbon accounting, timber valuation, forest growth and yield modeling, and forest ecosystem analysis. The proposed model needs to be applied cautiously for forest conditions not covered by model fitting data and model testing data. Model improvement may be possible through recalibration with additional data collected from wider



Annex 1b. Model curves overlaid on the measured tree volume data for *Cedrus deodara*. With the variation of predictor variable total height of the tree from about minimum to maximum values in the measured data, tree volume significantly varied. The Left appears biologically more logical than the right.

distributions of the species of interest across Karnali province or beyond and application of more robust modeling appraoches, such as mixed-effects modeling and machine learning.

CRediT authorship contribution statement

Kamal Raj Aryal: Conceptualization, Methodology, Investigation, Data curation, Software, Formal analysis, Visualization, Writing – original draft, Validation, Writing – review & editing, Project administration. **Tolak Raj Chapagain:** Methodology, Data curation, Software, Validation, Writing – original draft, Writing – review & editing. **Rajendra Kumar Basukala:** Investigation, Project administration. **Sabitra Khadka:** Investigation, Project administration. **Gopiram Chaudhary:** Investigation, Project administration. **Ram Krishna Budha:** Investigation, Project administration. **Hari Adhikari:** Writing – review & editing. **Dinesh Jung Khatri:** Investigation, Data curation. **Upendra Aryal:** Investigation, Data curation. **Ram P. Sharma:** Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors thank Forest Research and Training Center (FRTC), Karnali Province, Surkhet, Nepal, for making data available for this work and for the partial financial arrangement to accomplish the works (Project reference number: 01/2078/2079).

Annex

Annex 1a
Annex 1b

References

Akaike, H., 1972. A new look at statistical model identification. IEEE Trans. Autom. Control AC19 (6), 716–723.
Assmann, E., 1970. The Principles Of Forest Yield Studies. Pergamon press, Oxford, p. 506.
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: Internat. J. Forest Res. 95, 405–415.
Biazatti, S.C., Môra, R., Sccoti, M.S.V., de Brito Júnior, J.F., dos Santos Queiroz, N., de Angeli Curto, R., 2020. Criterion Dendrometer as a non-destructive method for dendrometric estimations of native species in Western Amazon. Revista Ibero-Americana de Ciências Ambientais 11 (6), 59–70.
Bishowkarma, R., Sharma, R.P., Bhandari, S., 2019. A generalized aboveground biomass model for juvenile individuals of Rhododendron arborium (Sm.) in Nepal. Cerne 25, 119–130.
Buckley, T.N., Cescatti, A., Farquhar, G.D., 2013. What does optimization theory actually predict about crown profiles of photosynthetic capacity when models incorporate greater realism? Plant Cell Environ. 36 (8), 1547–1563.
Burnham, K.P., Anderson, D.R., 2002. Model selection and inference: A practical information-theoretic approach. Springer-Verlag, New York.
Chapagain, T.R., Sharma, R.P., 2021. Modeling form factors for sal (Shorea robusta Gaertn.) using tree and stand measures, and random effects. For. Ecol. Manage. 482, 118807.
Chapagain, T.R., Sharma, R.P., Bhandari, S.K., 2014. Modeling above-ground biomass for three tropical tree species at their juvenile stage. Forest Sci Technol 10 (2), 51–60.
Chaturvedi, A.N., Khanna, L.S., 2011. Forest mensuration and biometry, 5th ed. Khanna Bandhu, Dheradun, India.
Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., Bailey, R.L., 1983. Timber management: a quantitative approach. Wiley, New York, p. 333.

Crecente-Campo, F., Tomé, M., Soares, P., Diéguez-Aranda, U., 2010. A generalized nonlinear mixed-effects height-diameter model for Eucalyptus globulus L. in northwestern Spain. For. Ecol. Manage. 259 (5), 943–952.
Cysneiros, V.C., Gaui, T.D., Silveira Filho, T.B., Pelissari, A.L., Machado, S.D.A., de Carvalho, D.C., Moura, T.A., Amorim, H.B., 2020. Tree volume modeling for forest types in the atlantic forest: Generic and specific models. IForest 13, 417–425. https://doi.org/10.3832/ifor3495-013.
Dfrs, 2015. State of Nepal's Forests. Department of Forest Resource and Survey, Kathmandu.
Dhm, 2017. climate trend analysis in the districts and physiographic regions of Nepal (1971–2014). Department of Hydrology and Meterology, Kathmandu, Nepal. Issue June.
Domke, G.M., Oswalt, C.M., Woodall, C.W., Turner, J.A., 2013. Estimation of Merchantable Bole Volume and Biomass above Sawlog Top in the National Forest Inventory of the United States. J. For. 111 (6), 383–387.
Forrester, D.I., Dumbrell, I.C., Elms, S.R., Paul, K.I., Pinkard, E.A., Roxburgh, S.H., Baker, T.G., 2021. Can crown variables increase the generality of individual tree biomass equations? Trees 35 (1), 15–26.
Gimenez, B.O., dos Santos, L.T., Gebara, J., Celes, C.H.S., Durgante, F.M., Lima, A.J.N., Santos, J. dos, Higuchi, N., 2017. Tree climbing techniques and volume equations for Eschweilera (Matá-Matá), a hyperdominant genus in the Amazon Forest. Forests 8. https://doi.org/10.3390/f8050154.
Gschwantner, T., Alberdi, I., Balázs, A., Bauwens, S., Bender, S., Borota, D., Bosela, M., Bouriaud, O., Cañellas, I., Donis, J., Freudenschuß, A., Hervé, J.C., Hladnik, D., Jansons, J., Kolozs, L., Korhonen, K.T., Kucera, M., Kulbokas, G., Kuliešis, A., Lanz, A., Lejeune, P., Lind, T., Marin, G., Morneau, F., Nagy, D., Nord-Larsen, T., Nunes, L., Pantić, D., Paulo, J.A., Pikula, T., Redmond, J., Rego, F.C., Riedel, T., Saint-André, L., Šebeň, V., Sims, A., Skudnik, M., Solti, G., Tomter, S.M., Twomey, M., Westerlund, B., Zell, J., 2019. Harmonisation of stem volume estimates in European National Forest Inventories. Ann. For. Sci. 76 https://doi.org/10.1007/s13595-019-0800-8.
Hirsch, R.P., 1991. Validation samples. Biometrics 47, 1193–1194.
Hogg, B.W., Lewis, T., Huth, J.R., Lee, D.J., 2021. Small-tree volume equations for subtropical hardwood plantation species. Aust. For. 84 (3), 152–158.
Hosoda, K., Iehara, T., 2010. Abovegroud biomass equations for individual trees of Cryptomeria japonica, Chamaecyparis obtusa and Larix kaempferi in Japan. J. For. Res. (Harbin) 15, 299–306.
Huxley, J.S., Teissier, G., 1936. Terminology of relative growth. Nature 137 (3471), 780–781.
IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories, Volume 4. Agriculture Forestry and other land use, In Egglesstons.
Jackson, J.K., 1994. Manual of afforestation in Nepal. Forest research and survey center, Ministry of forest and soil conservation, Nepal.
Kachamba, D.J., Eid, T., 2016. Total tree, merchantable stem and branch volume models for miombo woodlands of Malawi. Southern Forests J. Forest Sci. 78 (1), 41–51.
Kershaw, J.A., Ducey, M.J., Beers, T.W., Husch, B. (Eds.), 2017. Forest Mensuration. Wiley.
Kim, H.-J., Lee, S.-H., 2016. Developing the volume models for 5 major species of street trees in Gwangju metropolitan city of Korea. Urban For. Urban Green. 18, 53–58.
Ko, C., Kang, J.T., Son, M., Kim, Y., D.-G. E., 2019. tree volume using stem taper equation for Quercus mongolica in South Korea. Forest Sci Technol 15, 58–62.
Kozak, A., Kozak, R., 2003. Does cross validation provide additional information in the evaluation of regression models? Can. J. For. Res. 33 (6), 976–987.
LASERTECH., 2109. Laser Technology, Inc. Criterion® RD 1000. LASERTECH, 2019.
Lee, D., Seo, Y., Choi, J., 2017. Estimation and validation of tree volume equations for Pinus densiflora, Pinus koraiensis, and Larix kaempferi in South Korea. Forest Sci Technol 13, 77–82.
Lindner, M., Karjalainen, T., 2007. Carbon inventory methods and carbon mitigation potentials of forests in Europe: a short review of recent progress. Eur. J. For. Res. 126 (2), 149–156.
MacFarlane, D.W., 2011. Allometric scaling of large branch volume in hardwood trees in Michigan, USA: implications for aboveground forest carbon stock inventories. For. Sci. 57, 451–459.
Mandal, R., Khadka, G., Shrestha, M., Sah, S., 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. Discovery 56, 239–253.
Marquardt, D.W., 1963. An algorithm for least-squares estimation of non-linear parameters. J. Soc. Indust. Appl. Math. 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 J. Forest Sci. 76 (4), 209–219.
McRoberts, R.E., Tomppo, E.O., Schadauer, K., Ståhl, G., 2012. Harmonizing national forest inventories. For. Sci. 58, 189–190. https://doi.org/10.5849/forsci.12-042.
McRoberts, R.E., Westfall, J.A., 2016. Propagating uncertainty through individual tree volume model predictions to large-area volume estimates. Ann. For. Sci. 73 (3), 625–633.
Montgomery, D.C., Peck, E.A., Vining, G.G., 2012. Introduction to Linear Regression Analysis, 5th ed. John Wiley and Sons Inc.
Pinheiro, J.C., Bates, D.M., 2000. Mixed-Effects Models in S and S-PLUS. Springer, New York.
Planck, V.R.N., MacFarlane, D.W., 2014. Modelling vertical allocation of tree stem and branch volume for hardwoods. Forestry: Internat. J. Forest Res. 87, 459–469.
SAS_Institute_Inc., S. 9. 4, 2016. User's Guide. SAS Institute Inc, Cary, NC.
Schumacher, F.X., 1939. A new growth curve and its application to timber yield studies. J. For. Res. (Harbin) 37, 819–820.
Sharma, R.P., Brunner, A., Eid, T., Øyen, B.-H., 2011. Modelling dominant height growth from national forest inventory individual tree data with short time series and large age errors. For. Ecol. Manage. 262 (12), 2162–2175.
Sharma, E.R., Pukkala, T., 1990. Volume and biomass prediction equations of forest trees of Nepal. Forest Survey And Statistical Division, Ministry of Forest And Soil Conservation, Nepal.
Sharma, R.P., Vacek, Z., Vacek, S., 2016. Individual tree crown width models for Norway spruce and European beech in Czech Republic. For. Ecol. Manage. 366, 208–220.
Sharma, R.P., Vacek, Z., Vacek, S., 2018. Generalized Nonlinear Mixed-Effects Individual Tree Crown Ratio Models for Norway Spruce and European Beech. Forests 9, 555.
Sharma, R.P., Vacek, Z., Vacek, S., Ku cera, M.,, 2019. Modelling individual tree height–diameter relationships for multi-layered and multi-species forests in central Europe. Trees 33, 103–119.
Shrestha, H., Kafle, M., Khanal, K., Mandal, R., Khanal, K., 2018b. Developing local volume tables for three important tree species in Nawalparasi and Kapilvastu districts. Banko Janakari 27, 84–91.
Shrestha, D.B., Sharma, R.P., Bhandari, S.K., 2018a. Individual tree aboveground biomass for Castanopsis indica in the mid-hills of Nepal. Agrofor. Syst. 92 (6), 1611–1623.
Silwal, R., Baral, S., Chhetri, B., 2018. Modeling taper and volume of Sal (Shorea robusta Gaertn. f.) trees in the western Terai region of Nepal. Banko Janakari 27, 76–83.
Štícha, V., Sharma, R.P., Vacek, Z., Vacek, S., Nuhlíček, O., 2019. Timber and branch volume prediction: Effects of stand and site characteristics on dendromass and timber-to-branch volume ratio of Norway spruce in managed forests. Forests 10 (2), 144.
Subedi, T., 2018. Volume models for Sal (Shorea robusta Gaertn.) in far-western Terai of Nepal. Banko Janakari 27, 3–11.
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.
Thapa, T., Upadhyaya, C., Timilsina, Y., Bhandari, S., Puri, L., 2012. Modelling Tree Volume Of Pinus Roxburghii From Midhill Region Of Nepal. Himalayan Scientific Journal 5, 1–5.
Tiwari, A., Thapa, N., Aryal, S., Rana, P., Adhikari, S., 2020. Growth performance of planted population of Pinus roxburghii in central Nepal. J Ecol Environ 44, 31.
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. J For Res (Harbin) 33 (6), 1725–1737.
Weiskittel, A.R., Hann, D.W., Kershaw, J.A., Vanclay, J.K. (Eds.), 2011. Forest Growth and Yield Modeling. Wiley.
Wirth, C., Schumacher, J., Schulze, E.-D., 2004. Generic biomass functions for Norway spruce in Central Europe–a meta-analysis approach toward prediction and uncertainty estimation. Tree Physiol. 24 (2), 121–139.
Yang, Y., Monserud, R.A., Huang, S., 2004. An evaluation of diagnostic tests and their roles in validating forest biometric models. Can. J. For. Res. 34 (3), 619–629.
Zarnoch, S.J., Bechtold, W.A., Stolte, K.W., 2004. Using crown condition variables as indicators of forest health. Can. J. For. Res. 34 (5), 1057–1070.
Zeide, B., 1993. Analysis of growth equations. For. Sci. 39, 594–616.
Zhang, L., 1997. Cross-validation of non-linear growth functions for modelling tree height-diameter relationships. Ann. Bot. 79, 251–257.