Research paper

Modeling the tree height-diameter relationship in natural forests of *Cedrus deodara* in the Pakistani Himalayas

Minhas Hussain[1,4], Rospita Odorlina Pilianna Situmorang[2], Kashaf Amir[3]

【Summary】

Tree modeling is a common technique used in forestry where tree biometrics are linked to one another to predict the value of a difficult parameter such as biomass as a function of an easier parameter, commonly the diameter at breast height (DBH) and/or height. The present study was conducted in Swat District, a moist temperate mountainous Himalayan region of Pakistan where 5 sampling plots were installed to collect data. The primary purpose of this study was to develop a tree height-estimating model as a function of DBH for Cedrus deodara (deodar) in its natural habitat. The second purpose, which was linked to the primary purpose, was to evaluate model accuracy by comparing predicted tree heights (H) given by the H-DBH model with actual heights of the species measured in field surveys. This study employed 5 functions in an attempt to develop an H-DBH model. These functions were a linear regression (LR) function, logarithmic function (LF), power function (PF), quadratic function (QF), and exponential function (EF). Parameters for the regression models were obtained through the least squares method. The power function outperformed all other functions with the highest adjusted R^2 value (0.894) and lowest residual standard error (0.086) and was considered to be the model with the highest goodness of fit with the highest accuracy of tree height predictions. The selected PF model was applied to the DBH of field data to predict tree heights which were then compared to actual tree heights using t-test statistics. Respective field-measured height values of plots 1 thru 5 were 19.335 ± 3.388, 18.475 ± 3.690, 26.503 ± 6.355, 26.783 ± 4.866, and 27.849 ± 2.806 m, while respective predicted height values for plots 1 thru 5 were 19.165 ± 3.114, 18.500 ± 3.178, 26.497 ± 5.177, 26.558 ± 3.803, and 27.751 ± 2.411 m. Comparing actual and model heights using a *t*-test (p value ≥ 0.832 for all plots) showed that height values for each corresponding plot did not significantly differ.

Key words: allometric models, *Cedrus deodara*, tree height, Himalayan moist temperate forest.

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研究報告

以巴基斯坦喜馬拉雅山天然林之雪松模擬樹高-胸徑關係

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摘　要

樹木建模是林業中常用的技術，其中樹木生物學特性相互關聯以預測生物量等困難參數的值作為更簡單參數 (通常是胸徑 (DBH) 和樹高 (H)) 的函數。 本研究是在巴基斯坦濕潤溫帶喜馬拉雅山的斯瓦特地區進行的，共設置五個採樣點收集數據。本研究主要目的在於建立模型，用於估計樹高 (H) 與自然棲息地中雪松 (deodar) 的胸徑 (DBH) 的函數關係，另與主要目標相關的第二個目標是通過比較 H-DBH 模型給出的預測H與實地調查中測量的物種的實際高度來評估模型的準確性。本研究使用五個函數來開發 H-DBH 模型。這些函數是線性回歸函數(LR)、對數函數(LF)、冪函數(PF)、二次函數(QF) 和指數函數(EF)。回歸模型的參數通過最小二乘法獲得。冪函數優於所有其他具有最高 R^2 值 (0.894) 和最低殘差標準誤差 (0.086) 的函數，被認為是具有高擬合度和高準確度的模型。將選定的 PF 模型應用於現場數據的 DBH 以預測樹高，然後使用 t 檢驗統計將其與實際樹高進行比較。 樣點1至樣點5的現場實測高度值分別為19.335±3.388、18.475±3.690、26.503±6.355、26.783±4.866、27.849±2.806 m、而樣點1至樣點5的預測高度值為19.165±3.114、18.500±3.170、26.497±5.177、26.558±3.803、27.751±2.411 m。t 檢驗結果顯示使用模型做出的預測與實際樹高沒有顯著差異 (p-value ≥ 0.832)。

關鍵詞：異速生長模型、雪松、樹高、喜馬拉雅濕潤溫帶森林。

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INTRODUCTION

Accurate allometric estimations are useful in forestry not only for yield estimation but also for forest management and understanding carbon and other nutrient cycling pathways. The trend of developing allometric models in forestry has increased over the past few decades, and it has further been accelerated by the inclusion of climate change considerations that require greater accuracy in predicting carbon storage in a particular ecosystem (Temesgen et al. 2015). Tree modeling is a common technique in forestry which is used to develop models based on tree biometric properties. Tree biometric information such as tree height (H), diameter at breast height (DBH), bark thickness, volume, and wood basic density are prominent variables necessary to establish tree biometric models known as allometric models. Tree allometry links some key biometric variables usually easily measurable such as DBH with some other tree variables that are often difficult to directly measure, such as height and biomass (Cienciala 2006). Tree allometry is used to set up statistical relations based on detailed field measurements taken from sampling plots and which is later used to generate predictions for other individual trees or whole forest stands based on a single, readily measurable variable such as DBH or in some cases using multiple variables such as DBH and height (Cutini et al. 2013). These models help extract information needed to make forest management decisions based on potential future yields predicted by models (Van Laar and Akça 2007). Applying allometric models is also economical as they give quick and reliable estimates which otherwise could be time-consuming and costly (West 2009). Furthermore, allometric models are the most important tools for evaluating structural and functional changes that occur in a forest state over time (Dubayah et al. 2010, Bustamante et al. 2016).

As a tree grows, the major components such as height and DBH increase except for tree-specific gravity which remains constant, and it only varies from species to species. These continually growing tree variables are useful for developing models as they link difficult tree parameters such as tree height, tree biomass, or carbon storage to an easily measurable variable such as DBH (Nizami 2014, Hussain et al. 2021, Brede 2022). One such important relationship is the H-DBH relationship which is used to predict tree height with reference to the widely used tree parameter, DBH (Narmontas et al., 2020). The DBH and total tree height are fundamental single-tree parameters that describe the forest structure and other characteristics (Chave et al. 2014). Both are generally used as independent variables for tree volume, biomass estimations, tree growth, and yield modeling (Mugasha et al. 2019). DBH is the easiest measurable tree variable; however, field measurements of tree height are a comparatively challenging task particularly when trees are tall, crowns are dense, and the terrain is sloping. In such conditions, tree height measurements mostly rely upon the traditional method of using H-DBH models that relate tree height growth with DBH increments (Curtis 1967, Mokria et al. 2015, Zea-Camaño et al. 2020). Predictions of height are crucial for estimating forest parameters like the biomass and volume of a tree or stand. The accuracy of predictions depends upon the prediction capacity of the applied model which can vary from model to model and species to species and can be influenced by the size and range of the sampling data (Mugasha et al. 2019). These allometric models have different statistical forms such as linear, exponential, logarithmic, power, etc. and can be functionally generalized for mixed forest types or be specific for pure or plantation forest types (Hussain et al. 2021).

Cedrus deodara (deodar), the target species of this study, is a conifer native to Pakistan, India, Nepal, and Afghanistan. It has been introduced to Argentina, Canada, China, France, Germany, Italy, and Spain where it has been planted in vast areas (Orwa et al. 2009). *Cedrus deodara* is native to the Himalayas, where it thrives within an elevation range of 1100~3600 m, preferably growing in temperate forests, but it is distributed across a range of climatic zones (Univ of Redlands 2022). It is a large conifer tree that can reach up to 40~60 m in height, and the DBH can exceed 1 m and exceptionally reaches up to 3 m in its natural habitat (Sheikh 1993, Pijut 2000). It is an evergreen and fast-growing conifer that has an average annual increment of 0.7–0.90 m yr^{-1} which is a relatively fast-growing species among cedar species (Kalliergeia 2022). Having the status of the national tree of Pakistan, this species occupies a dominant position in dry temperate forests of the country, although it also exists in moist temperate regions of the country (Ali et al. 2016). However, it thrives best in montane forests and is also distributed in other Himalayan topographic regions. It has an elevation range of 1700~3000 m in western regions and

1300~3300 m in eastern regions with a less dry climate (Raqeeb et al. 2020).

Several studies regarding tree modeling of *C. deodara* were conducted in Pakistan. Raqeeb et al. (2020) developed volume and biomass equations for *C. deodara* growing in natural temperate forests of the Himalayan region. They used a destructive sampling technique to directly measure the biomass and basic wood density which were used to build a model for biomass estimations. Ali et al. (2016) also developed a local allometric equation only for biomass estimation of *C. deodara* in dry temperate forests of northern Pakistan, using destructive sampling. Ahmed and Sarangezai (1991) used a dendrochronological approach to estimate the age and average annual increment of various species including *C. deodara* in the Himalayan region. Most of these previously developed models were either for biomass, volume, or age predictions, but none of them addressed tree height. That is the reason, to date, there is no model available for estimating *C. deodara* height in natural Himalayan forests, where steep and undulating mountainous terrains make the tree height measurement process very slow, complicated, and inefficient in terms of time and cost. To make this data acquisition process more efficient, H-DBH models are direly needed.

Recognizing the urgent need for reliable tree height models for Himalayan montane forests and to enhance the speed of the tree-height data collection process for future researchers, this study was designed. This is the first ever attempt to develop a species-specific tree-height model for Himalayan deodar using empirical data obtained from natural *C. deodara* forests in the moist temperate Himalayan region of Pakistan. Merely constructing a biometric model is insufficient; it must be reliable enough to be extrapolated for future use. Therefore, model testing for reliability was also included as an extended purpose of this study which was carried out by comparing model-predicted heights with actual tree heights using the *t*-test.

MATERIALS AND METHODS

Study area description

The study was conducted in the Swat District of Khyber Pakhtunkhwa (KPK) province of Pakistan which is comprised of a very rugged mountainous topography. This region is located in the temperate zone, where various factors such as elevation, latitude, the Indian Ocean monsoon, and westerly storm currents control the climate. June is the hottest month and January the coldest month in this region. The average annual rainfall in this area is 1000~1200 mm (IAO and Government of Khyber Pakhtunkhwa 2013, Bacha et al. 2021). Specifically, the upper part of the Swat District in the Kalam valley is mountainous terrain that may experience a maximum temperature of up to 37 °C in June to as low as –18.2 °C in January (Dahri et al. 2011). Sampling plots were installed in 4 different sites at Kalam, the Hariania valley, Asrait, and Bahrain which are several kilometers separated from each other (Fig. 1). The geographic location of each plot is given in Table 1. Being part of the Himalayas, all of the regions have a mountainous topography. The climate is moist and temperate in the upper regions of Kalam. However, precipitation gradually decreases moving downwards towards Bahrain. The elevation of the Kalam region of Swat is 2103.01 m (Bangash et al. 2018). Details of the coordinates of each sampling plot are given in Table 1.

Species composition

Kalam forests are often heterogeneous and consist of a wide range of species in-

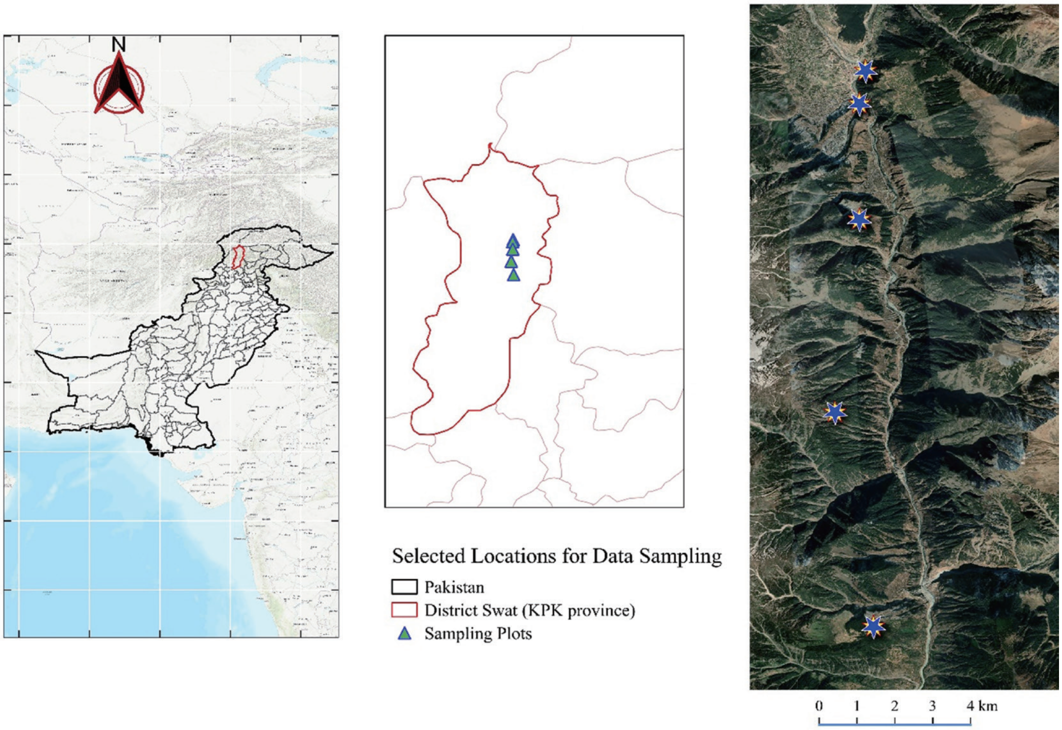

Fig. 1. Study area and locations of sites where sampling plots were installed.

Table 1. A geographic description of plots including stem numbers

Plot no.	Landmark	Stems	Latitude (N)	Longitude (E)
1	Kalam	33	35.477	72.595
2	Kalam	29	35.468	72.593
3	Hariania	19	35.434	72.593
4	Asrait	16	35.376	72.586
5	Bahrain	28	35.313	72.597

cluding native conifers and both natural and planted broadleaf species (Kalam Forest Division Madyan Swat 2014). Tree species are distributed in a horizontal pattern where natural broadleaf species such as *Quercus incana* (bluejack oak) and *Q. dilatata* (green oak), and planted species such as *Populus nigra* (poplar), *Moral alba* (mulberry), and *Juglans regia* (walnut) are distributed on nearby riverbanks and residential areas, while *Quercus* species are found growing at the lower boundaries of *C. deodara* forests. Conifers, particularly *C. deodara,* are robust dominant species that constitute major forest cover and are omnipotent species of the Kalam forest. Other conifers species such as *Pinus wallichiana* (kail), *Abies pindrow* (fir), and *Picea smithiana* (spruce) are mixed with *C. deodara*

Fig. 2. Species composition of the sites. Conifers were distributed above the residential area, while broadleaf species were found in nearby residential areas and riverbanks.

Table 2. Characteristics of the sampling plots

Plot no.	DBH(cm)		Height(m)		Density (stems ha^{-1})
	Mean	SD	Mean	SD	
1	42.437	16.566	19.335	3.338	550
2	38.769	17.363	18.475	3.690	483
3	107.181	45.915	26.502	6.355	317
4	104.090	38.764	26.782	4.865	267
5	114.426	28.020	27.838	2.806	467

SD, standard deviation.

in higher elevations above pure *C. deodara* stands. Fig. 2 shows the forest distribution pattern of the Kalam region where data were collected.

Data collection

Five sampling plots were established in 4 different locations, and a survey was conducted in April 2019. The size of each plot was 600 m^2 with a length of 30 m and a breadth of 20 m. The first 2 plots were in the upper Kalam valley and were adjacent to each other. The rest of the plots were far from each other and were installed in different valleys. Because of their close proximity, trees in the first two plots had similar density, DBH, and H ranges. Comparatively, the stem density of this location was far higher than at the 3 other locations; however, the mean DBH and mean height were smaller than those of the other 3 plots as illustrated in Table 2.

Sampling for *C. deodara* data collection was carried out in each plot in which DBH and total height (H) of all the trees were measured. Overall, 125 stems that were sampled were used to construct an H-DBH model. DBH was measured with the help of tree calipers, while H was measured with a Haga altimeter. The Haga altimeter directly measures tree height from fixed distances of 15, 20, 25, and 30 m from the tree. The calibrated scale of the Haga altimeter is set according to the selected range and then it tells the tree height value. The range of subject trees to the observer was calculated using a measuring tape. For the sake of reducing bias from the H-DBH model, trees with a DBH of < 8 cm were not included. The statistical analysis was carried out in the R statistical environment vers. 4.1.3 (R Core Team 2022) and SPSS (vers. 26, IBM, Armonk, NY, USA).

Research framework

The framework of this study was based on the purpose of developing a reliable model for height estimations of *C. deodara* in its natural habitat. To achieve this task, 5 allometric functions, namely a linear regression (LR) function, logarithmic function (LF), quadratic function (QF), power function (PF), and exponential function (EF), were employed to run the tree DBH and height data. The LR function is often used in data analysis and empirical modeling in fields such as forestry. However, the growth pattern of trees is heteroscedastic and changes with age and with rapid growth in early stages of development

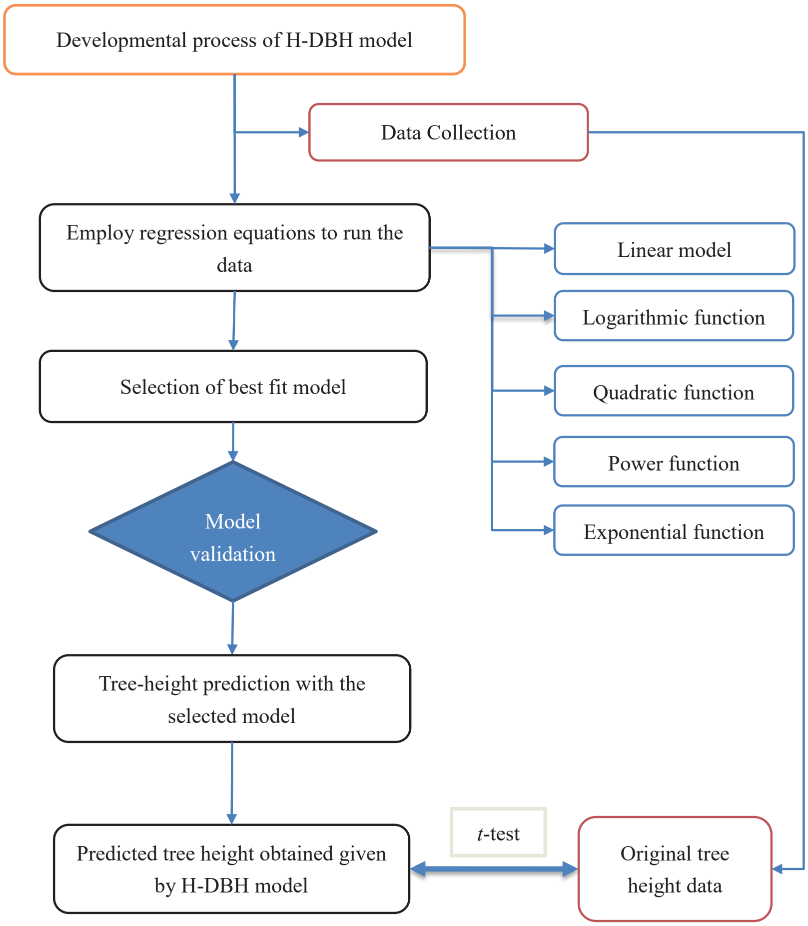

Fig. 3. Framework of the study.

followed by a gradual retardation (Bowman et al. 2013). The LR function does not always adequately account for these variations, and so nonlinear functions are also important for modeling tree biometrics in forestry. Hence, both linear and non-linear functions are used in forestry, and there are no hard and fast rules for choosing a function. Therefore, we used 5 functions including the LR to determine the most suitable function for developing a tree-height model for *C. deodara.*

The selection of models was based on their value of the adjusted R^2 (adj. R^2), where the model with the highest adj. R^2 value was considered the best fit. Further, the selected H-DBH model was validated by applying the model to DBH data of each plot to predict heights and compare predicted heights with actual heights obtained from fieldwork. Comparisons were tested with the *t*-test statistics. The detailed framework is shown in Fig. 3.

Tree height estimating models

As tree height is an important component of other growth and yield models, accurate prediction of tree height is usually desired. Multiple models to estimate tree height were included to understand and extract real patterns of tree height increments and the relationship to DBH. Below are the functions used to evaluate H-DBH proportional relations.

Linear regression (LR): Y= $\alpha \times \beta$X; (1)

where Y is tree height, X is DBH, α is the intercept, and β is the slope of the regression. The regression used here was the ordinary least squares which uses the least square method to predict its parameters.

The linear model illustrates the H-DBH as being constant. However, the H-DBH relationship is not static, but rather it varies with the age of the tree, which a linear model cannot explain (Narmontas et al. 2020). To satisfy this situation, this study included nonlinear models. Exponential regression models are commonly used in growth studies (Neter et al. 2005) where the rate of H growth at a given time is proportional to the DBH increment. The second model here is the exponential function (equation 2).

Exponential function (EF):$Y=\gamma_o \times e^{\gamma 1X}$. (2)

The third function used was a logarithmic function given as:

Logarithmic function (LF): $Y=\gamma_o+\gamma_1 \ln(X)$; (3)

where ln is the natural logarithm.

The fourth competitor model was the power function, which has the following form:

Power function (PF): $Y=\gamma_o \times X^{\gamma 1}$. (4)

In functions 2–4, Y is the tree total height, X is DBH, and γ_o and γ_1 are parameters.

A second-degree polynomial function was also used which has the following form:

Quadratic function (QF): Y= $a+bx+cx^2$; (5)

where a, b, and c are non-zero numbers called constants which are coefficients of the polynomial.

Model reliability assessment

These models were compared based on their adj. R^2 value which is the coefficient of determination. The adj. R^2 is the statistical measurement that illustrates the proportion of variance for the dependent variable explained by the independent variable in a regression equation; in other words, it shows the goodness of fit of a regression model (Miles 2005). Its value ranges from 0 to 1, where 1 represents a perfect fit. Increasing the R^2 value closer to 1 increases the reliability of the model. In regression analyses, R^2 is computed as follows:

$$R^2 = 1 - \frac{RSS}{TSS}; \quad (6)$$

where R^2 is the coefficient of determination, RSS is the sum of squares residual, and TSS is the total sum of squares.

Comparison of predicted and actual tree heights

This comparison was based on hypothesis testing using t-test statistics. The null hypothesis (H0) here states that there was no significant difference between the predicted height and actual height, while the alternative hypothesis (H1) states that the means of the actual tree height and predicted tree height in each plot significantly differed. For this test, the selected highly reliable model was first applied in each plot to estimate the height of each *C. deodara* tree, and then the mean height of each tree was measured. The t-test statistics were then applied to compare means of both the predicted and actual tree height values. This test helped validate the model and its reliability on practical grounds. If the H0 was rejected in case of a significant difference between the 2 means, then the model cannot predict the tree height and vice versa. The level of significance of the *p* value for the *t*-test was 0.05.

RESULTS

Site description

Four sites were selected, and 5 plots were established. These sites were at different elevations and several kilometers away from each other. These differences in sampling sites were also reflected by stand characteristics in the plots. The first 2 plots which were adjacent to each other had similar stand characteristics such as mean DBH, mean H, and respective standard deviations (SDs), and their stem densities were very closely related. Trees in these plots had relatively lower DBH values compared to the other plots. Plot 2 had the smallest mean DBH, while the maximum mean DBH was calculated in plot 5. The DBH and H of the last 3 plots were closely related. Nevertheless, variations in their SDs were quite high.

The maximum tree height was calculated in plot 5 which was 27.85 m, while the minimum tree height was found in plot 2 at 18.48 m. Densities in these sites also greatly differed from each other. Overall, the minimum stand density was observed in plot 4 with around 267 stems ha^{-1} while the maximum stand density was observed in plot 1 at 550 stems ha^{-1}. From Table 2, it can be observed that variations in site productivity of *C. deodara* forests in the selected locations were very pronounced. Therefore, it was necessary to select stems with a wide DBH range for sampling in order to ensure the reliability of the H-DBH model and make it applicable for wide ranges of DBH classes, elevations, stand densities, and ages.

Model fitting for tree height

To develop and select a reliable model for tree H estimations, data for tree height and DBH were run with the 5 above-mentioned allometric equations. All functions contained 2 model parameters (slope and intercept), except the quadratic function which is a second-degree function where the slope is managed by combining 2 parameters. In Table 3, it can be observed that the power function (PF) had the highest adj. R^2 value and had the lowest residual standard error (RSE), and was thus considered to be the best-fit model. The EF had the lowest value of adj. R^2 and was the least fit model compared to all others. The model with the highest RSE was LR. The *p* value for all

Table 3. Configuration of models used and statistical tests for evaluating their fitness

	Applied function	Developed models	RSE	Adj. R^2	*F*-statistics	*df*	*p* value
1	Power function	$5.1151\ x^{0.3582}$	0.086	0.894	1037	123	0.000
2	Quadratic function	$11.085 + 0.2151x - 0.0006x^2$	2.044	0.878	441.6	122	0.000
3	Logarithmic function	$-8.9112 + 7.7756\ln(x)$	2.186	0.867	755.6	123	0.000
4	Linear regression	$14.073 + 0.1195x$	2.3.00	0.845	670.5	123	0.000
5	Exponential function	$14.978\ e^{0.0053x}$	0.114	0.813	534.8	123	0.000

RSE, residual standard error; Adj., adjusted; *df*, degrees of freedom.

of the models was significant at a 0.001 level, showing that DBH and H were highly correlated. However, which models were best was decided by the adj. R^2 value and RSE.

Regression lines of all 5 prediction curves are presented in Fig. 4. The curves well explain the scattered dots representing actual tree height data and show strong correlations between DBH and tree height. Further, performances of the non-linear PF, LF, and QF curves were better than those of the linear and exponential curves. Both the LF and EF showed overestimations in higher DBH classes. Although all of the model curves showed

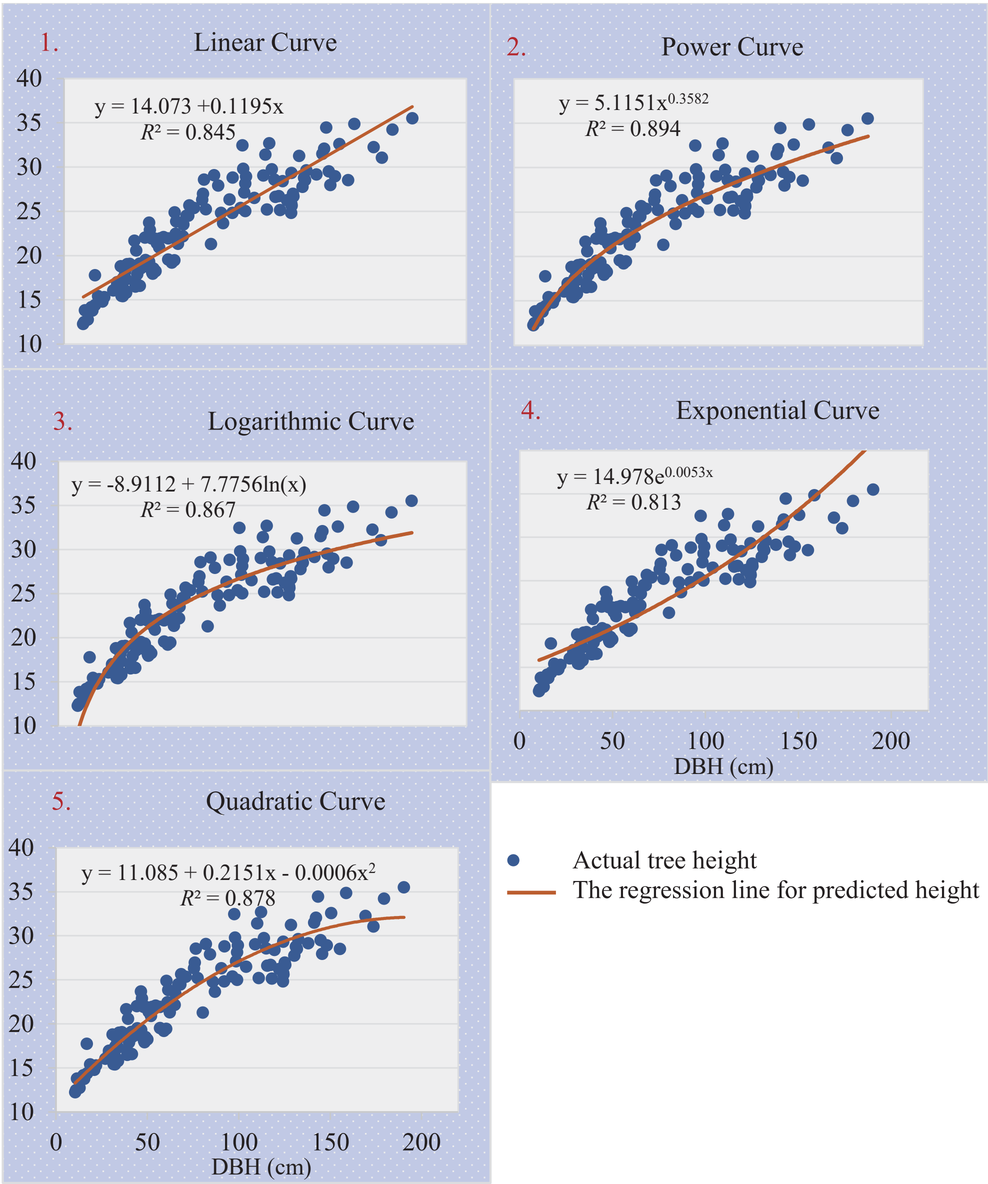

Fig. 4. Visual display of the height (H)-diameter at breast height (DBH) relationship evaluated by 5 allometric models.

a positive and significant correlation between tree height and DBH, the performance of the PF curve was particularly better than the rest as it provided the best explanation for tree height. This was also confirmed by the R^2 value which was highest for the PF and lowest for the EF as shown in Table 3.

Comparison of estimated height by models and original height data

The best-fit model selected for H-DBH estimations based on the highest R^2 value and lowest RSE was the PF model (Table 3). This model was employed to make tree height predictions for each plot of *C. deodara* natural stands. Predictions thus obtained were compared with original tree heights to evaluate the model precision and validation. These comparisons were carried out using independent-sample *t*-test statistics. Detailed comparisons of actual and predicted tree heights for each plot are shown in Table 4. Here Y represents the actual sample mean height, while Ŷ represents the predicted mean height of the same plot. The means and SDs of each compared pair were very close to each other and showed no significant difference. Homogeneity of variance was tested using Levene's test, and the *p* value of this test was > 0.05 for all plots. Thus, it was inferred that variances did not significantly differ from each other, and equal variances were assumed for both Y and Ŷ. Further, the *t*-test for comparing mean differences of the original and predicted heights for all 5 plots showed an insignificant difference with a *p* value of > 0.05. Hence, this test accepted the null hypothesis (H0) which stated that there was no significant difference between actual mean tree heights and mean predicted heights.

DISCUSSION

The trend of producing tree allometric models in Pakistan is comparatively slow. Even a model for tree height estimation for *C. deodara* is not yet available, although *C. deodara* was found to have the highest carbon mitigation potential compared to other major conifers such as *Abies pindrow, Pinus wallichiana,* mixed conifers, and open forests (Ahmad et al. 2019). This species has a high potential to absorb and store atmospheric carbon, yet its actual capacity is not well pre-

Table 4. Comparison of model predictions of mean tree heights (Y) with original mean tree heights (Ŷ) using *t*-test statistics

	Mean height				Levene's test		*t*-test				
Plot	Y	SD	Ŷ	SD	*F*	*p* value	*t* value	df	*p* value	Mean difference	SE difference
1	19.335	3.388	19.165	3.114	0.337	0.564	0.213	64	0.832	0.170	0.801
2	18.475	3.690	18.500	3.178	1.029	0.315	-0.027	56	0.978	-0.025	0.904
3	26.503	6.355	26.497	5.177	0.59	0.448	0.003	36	0.997	0.006	1.881
4	26.783	4.866	26.558	3.803	0.721	0.403	0.145	30	0.885	0.224	1.544
5	27.849	2.806	27.751	2.411	0.184	0.67	0.14	54	0.889	0.098	0.699

SD, standard deviation; df, degrees of freedom; SE, standard error.

dicted because of a lack of models (Ali et al. 2016), which is the reason why this study was conducted. Moreover, some previously conducted studies on biomass modeling strongly recommended conducting further research in this region for precise assessment of tree growth and yields for carbon storage (Nizami 2014), especially of moist temperate regions (Ali et al. 2016). The moist temperate region of Pakistan is enriched with different forest types dominated by conifers. That is the reason this study attempted to develop a model for *C. deodara* in the moist temperate region of the Pakistani Himalayas.

The topography of this region is mostly mountainous where the temperature is comparatively very low on the peaks and higher in the valleys, which might cause growth variations in tree species of the same genus at different elevations. Data collected from a single location could induce bias in model predictions. That was the reason behind collecting data from different sites at different elevations. The DBH range of sampling stems was kept large, ranging from 10 to over 200 cm, because if the data range increases, the prediction capacity of the model also increases, which covers a wide range of DBH classes. This is particularly useful to reduce model limitations and biases attached to it when applied beyond the range used to construct the model (Chave et al. 2005).

All 5 H-DBH models showed significantly high adj. R^2 values (i.e., minimum adj. R^2 = 0.813), thus all models explained more than 81% of total tree height variations, which implies that all these models were feasible for predicting *C. deodara* height. However, the PF model stood out from the others with the highest adj. R^2 value (0.894) explaining at least 89.4% of tree height variations and showing the best goodness of fit. Further, clarification was achieved from the RSE of each model. The PF exhibited the least RSE (of only 0.086) compared to all other functions further confirming its better performance. The R^2 value of the QF was also significantly high (0.878). Nevertheless, its RSE was also high (2.044), which decreased the model accuracy compared to PF. Details of the predicted regression lines and actual scattered data are shown in Fig. 4. Many studies showed similar results where a nonlinear function outperformed a linear function or where PF performed better than other functions. A previous study by Samalca (2007) also developed 5 models for forest biomass estimation that showed better performance by PF than by LR, QF, square root-transformed model, and multiplicative error PF models. When studying forest structures and regeneration patterns of juvenile and climax species mortality rates, Shimano (2000) found that PF better fit the distribution than EF. Similarly, when measuring the tree height of a moist tropical forest, Larjavaara and Muller-Landau (2013) found a better performance of the PF model exhibiting a lower root mean square error (RMSE) than the LR model.

Evaluation of the estimated height given by power function models and original height data

To test the selected PF model on practical grounds, this study compared estimated heights of trees with their respective tree heights in actual data. The insignificant results for Levene's test showed that variances in predicted heights and actual tree heights did not significantly differ in each plot. This provides insufficient evidence to reject the null hypothesis. Thus, there was not a significant difference between predicted and actual tree heights, and the H0 was accepted. Additionally, the *t*-test also found no significant difference between the mean of predicted heights and actual tree heights for each plot. A *p* value of > 0.8 was far higher than 0.05, illustrating the close result between the predicted and actual height values. Thus, this study inferred that predictions of tree heights were valid, and the PF model was viable.

For further studies of *C. deodara,* this H-DBH model could be used to indirectly measure tree height for time and cost reductions. Using this model will be helpful not only for time and cost savings but also for avoiding field measurements of height, which are difficult, particularly in mountainous terrain where finding a suitable flat and smooth distance range from a subject tree to the observer for height measurement is challenging and risky. This study is a small contribution toward tree modeling for yield estimations, particularly in the Himalayan region where allometric models for various tree species are scarce.

CONCLUSIONS

Development and analysis of 5 regression models of linear and non-linear types were fitted for tree height estimates of Himalayan *C. deodara* forests in the Swat District of Pakistan. All of the models significantly explained the proportional variance in tree height based on the DBH as a function. However, the adj. R^2 value for the power function (PF) model was highest along with the lowest RSE and was thus considered to be the best-fitting H-DBH model. Empirical testing of this model with actual height data further strengthened the best-fitting argument which was illustrated by the *t*-test for assessing mean differences, which showed no difference between predicted heights and actual heights for all plots. Thus, the outcome of this study is that the PF model outperformed the 4 other models in terms of model fitness and accuracy and was considered to be suitable for *C. deodara* height predictions. For the first time, an H-DBH model for Himalayan deodar was established, which is of great significance for future studies on volume estimations. It is particularly helpful because the habitat of *C. deodara* is mountainous terrain where field measurements of tree height are difficult and always come up with errors while trying to maintain accuracy. Using this model will ensure higher accuracy and help simplify the measurement of tree heights.

COMPETING INTERESTS

The authors declare no conflicts of interest.

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