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Estimation of *Fagus orientalis* Lipsky height using nonlinear models in Hyrcanian forests, Iran

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Abstract: Tree height is one of the most important variables in describing forest stand structure. However, due to difficulty in height measurement, especially in dense and mountainous forests, the common approach is to invoke the height-diameter (H-D) models. The oriental beech (*Fagus orientalis* Lipsky) is one of the most important species of Hyrcanian forests, over the mid to high-altitudes (400–1 800 m a.s.l.), in northern Iran. In this study, the H-D relationship of beech trees was investigated separately for mid-altitude and high-altitude in Shafaroud forests of Guilan using 14 nonlinear H-D models and an artificial neural network model (ANN). To collect data, a systematic random sampling method within a 100 × 100 m regular randomized grid was applied. In total, 3 243 individual trees in 255 circular plots with 0.1 ha were measured. For comparing the results, performance criteria including root mean square error (*RMSE*), R^2_{adj}, Akaike's information criterion (*AIC*), and mean absolute error (*MAE*) were used. In high and mid altitudes, Meyer (1940) and Bates and Watts (1980) models had the best performance, while Watts (1983) model and Burkhart-Strub (1974) model had the worst performance in high-altitude and in mid-altitude, respectively. On the other hand, the ANN model had the best accuracy and performance in both sites. Since the performance of the ANN model is superior and consistent compared to the common nonlinear models, here it is preferred for both regions.

Keywords: elevation; height-diameter modelling; neural network; oriental beech; Shafaroud

Forest management based on sustainable development principles requires accurate and practical data (Baumgartner 2019). The most significant quantitative data that provide suitable insight into the conditions of forest stands and have been used for sustainable forest management goals are diameter at breast height (*DBH*), height, and the relationship between them (Sharma, Breidenbach 2015). These two variables have shown the evolution and reaction of forest stands through time in response to the execution of previous management (Sharma et al. 2016a, 2019). As well as this, variables are used as inputs to tree growth, volume and site productivity (Zhang et al. 2020). Tree measuring in dense forest stands, mountainous areas, and highlands is complicated (Diamantopoulou et al. 2015), be-

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cause it increases measurement interruptions, and sampling hours, decreases accuracy, and ultimately increases costs (Mugasha et al. 2019).

Hyrcanian forests in northern Iran cover around 1.65 million ha and have uneven-aged structures, dense stands, and mountainous conditions (Nazari Sendi et al. 2014). These forests have valuable species such as oriental beech, European hornbeam, Caucasian alder, Persian ironwood, chestnut-leaved oak and lime tree (Nazari Sendi et al. 2020). Oriental beech (*Fagus orientalis* Lipsky) in northern Iran is distributed from Astara to the Golidaghi region. As the most valuable species, forest area (17.6%) and standing volume (23.6%) (Rasaneh et al. 2001), and in the Shafaroud basin (28% and 53%), forest planning is based on this species (Nazari Sendi et al. 2020). Although constant monitoring of beech stands is so important, measuring the tree height is difficult due to the size, density and steepness of beech stands. In this regard, the most significant technique forest experts and managers provide to solve this problem is height-diameter models (Temesgen, Gadow 2004).

As tree height increases nonlinearly with stem diameter (Zeide 1993), the nonlinear height-diameter (H-D) models estimate height from the diameter (Ng'andwe et al. 2019). Nonlinear regression models also have several advantages, such as producing biologically logical predictions, interpretability and parsimony, which means fewer variables are needed to discover the relationships between them (Mehtätalo et al. 2015).

Some studies of H-D relationship for different species in Hyrcanian forests have already been performed. Nazari Sendi et al. (2020) used the artificial neural network and nonlinear H-D models to estimate the height of the lime tree. The results showed that the artificial neural network model was more efficient than the nonlinear models.

After modelling and testing 18 nonlinear models for hornbeam in Shastkalateh forests of Gorgan (Golestan province, Eastern of Hyrcanian forests), Mohammadi and Shataee (2017) did not observe any significant difference between the applied models, but the hyperbolic, Ratkofsky, Richard-chapman and Weibull models were better predictors as compared to other models. Hassanzad Navroodi et al. (2016) showed that the Reed (1920) model for velvet maple in Asalem forests was more suitable than other models. Ahmadi et al. (2014) developed several nonlinear models for oriental beech in the middle of the Hyrcanian forests (Kajour, Mazandaran Province) demonstrating that Weibul, Schnute and Chapman-Richards functions provided the most satisfactory predictions of height. Scaranello et al. (2012) examined the H-D relationship of trees in the Atlantic tropics based on four sea-level elevations in Brazil. The results indicated that the altitude factor affected the estimation of the height of trees. To better manage the forest stands of two species of jack pine (*Pinus banksiana* Lamb) in Ontario, Canada, Zhang et al. (2002) investigated the effect of eco-region on the H-D relationship using the Chapman-Richards function as the best model. The important thing about using these relationships is that the use of these models may involve data extraction errors. Thus, their ability to estimate should be measured in advance (Thanh et al. 2019).

One of the methods that have overcome this problem, the usage of which has grown considerably in various fields in recent years, is artificial intelligence (Jordan, Mitchell 2015). Artificial neural network (ANN) models are nonlinear mapping structures inspired by the functioning of human brain (Hagan et al. 2014). They can model nonlinear relationships between input and output data without needing elaborated knowledge of the process under study. ANNs and their comparison with H-D models have also been used in some forest studies. In a study conducted by Castaño-Santamaría et al. (2013) in the uneven-aged beech forests of Spain, the ANN reduced the error rate by 22% compared to nonlinear regression.

There have been very few studies on H-D models for tree species at different environmental conditions in Iran. Due to the wide distribution of beech, it is necessary to conduct such a study on the efficiency of the model. In addition, the performance of nonlinear H-D models with ANN in different altitude classes has been compared only in one case so far (Nazari Sendi et al. 2020). Thus, the objectives of this study are: (*i*) to investigate the H-D relationship of oriental beech in the mid and high altitudes, (*ii*) to compare the results of nonlinear H-D models and ANN, and finally (*iii*) to determine the best model out of the evaluated models.

MATERIAL AND METHODS

Study area. This study was conducted in the Shafaroud watershed forests of Guilan province. Forests in the Shafaroud watershed are

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natural, uneven-aged with deciduous species dominated by oriental beech (*Fagus orientalis* Lipsky). The canopy cover of these forests is 80–85% and close to nature silviculture is used as the management method, while a single selection method was used in the previous decades. The geological substrates consist of acidic igneous rocks and the soil type in the whole area of the Shafaroud watershed is forest brown soil. The average annual temperature is 15.4 °C and the mean precipitation is 1 450 mm, the largest rainfalls occurring in spring and autumn. Due to maximum temperatures, relative air humidity is low and maximum relative air humidity occurs in the winter season (Nazari Sendi et al. 2020).

Oriental beech distribution ranges from mid to high altitudes and across different slope classes (10–80%). Even though the slope is one of the important environmental variables, in this study, no significant difference between the diameter and height of oriental beech was observed in the slope classes (less than 30%, 30–60%, and more than 60%). Oriental beech trees in two different regions were investigated based on altitude classes, namely district No. 7 in high-altitude (950–1 450 m) and district No. 16 in mid-altitude (500–950 m). In high altitude, this species is associated with the European hornbeam (*Carpinus betulus*), Caucasian alder (*Alnus subcordata*) and Persian ironwood (*Parrotia persica*), and in mid-altitude with chestnut-leaved oak (*Quercus castanefolia*) and lime tree (*Tilia begonifolia*). In district No. 7, two compartments (17 and 18) and in district No. 16, also two compartments (29 and 30) were investigated (Figure 1).

Data collection. In order to model the H-D relationship, the data from 255 sample plots were collected in the years 2019–2020. For this purpose, the systematic random sampling method and circular sample plots each with an area of 0.1 ha with 100 × 100 m regular randomized grid were used. In the plots, the geographical coordinates of trees

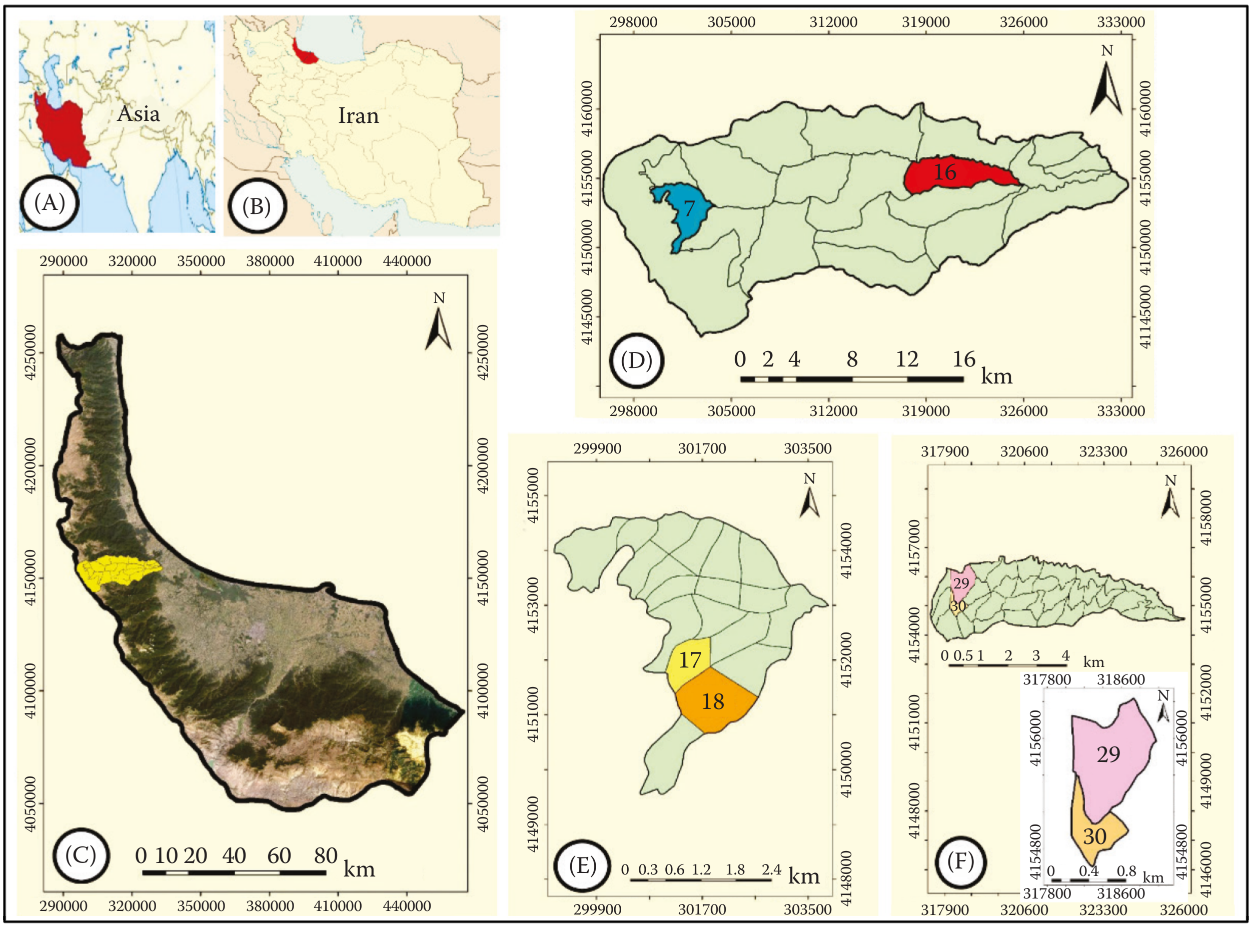

Figure 1. General location of the study area and location of the studied sites (A) Asia, (B) Iran, (C) Guilan province, (D) Shafaroud watershed, (E) district No. 7 (compartment 17 and 18), (F) district No. 16 (compartment 29 and 30)

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Table 1. Summary statistics of beech trees

Region	Data	No. of trees	Diameter				Height			
			mean	min	max	SE	mean	min	max	SE
High-altitude	total	1 467	33.6	7.5	152.5	36.8	14.6	3.3	38.2	9.7
	fitting	1 026	34.1	7.5	152.5	36.6	14.7	3.3	38.2	9.9
	evaluation	441	32.4	7.5	151.2	37.5	14.3	5.0	37.9	9.3
Mid-altitude	total	1 776	43.5	7.5	158.3	32.5	21.7	4.2	46.6	9.9
	fitting	1 243	43.4	7.5	158.3	30.8	21.8	6.0	46.6	9.8
	evaluation	533	43.8	7.5	152.5	36.1	21.4	4.2	44.9	10.3

SE – standard error

with centimetre accuracy from the plot centre and azimuth were recorded. *DBH* of oriental beech was measured using a caliper (Haglöf, Sweden) and height by employing Spiegel-relascope 'Silvanus' (Silvanus, Austria; Zobeiry 2005). Measuring the diameter at breast height (1.30 m) requires that the trees have reached a certain level of diameter growth.

Model development and comparison. The summary statistics of beech trees are presented in Table 1.

Height-diameter nonlinear models. Over the years, several models have been developed for estimating tree height. If this relationship is sigmoid, concave or close to it, nonlinear models can be used (Shen et al. 2020). First, 31 nonlinear models that had acceptable results in the same kind of studies were selected and for this purpose, we employed SigmaPlot (Version 14, 2018; Nazari Sendi et al. 2020). In order to model H-D relationship for beech, the data set was randomly divided into fitting (70%) and an evaluation (30%) data set. Following a review of the model findings based on estimated height and performance criteria, selected models are described in Table 2.

Artificial neural networks. The most fundamental kind of artificial neural network (ANN) is feed-forward multilayer perceptron (MLP) that consists of three layers: an input layer, one hidden layer, and an output layer. Each input has an associated weight and each output has an activation function (Maier, Dandy 2000). The input signals are propagated feed-forward through the network, layer after layer. The network topology consists of a set of nonlinear elements (neurons) connected by links and normally arranged in successive layers. Each neuron has a set of inputs. The purpose of the input layer is to pass on the values received to the neurons in the hidden layer (Kalteh 2017). The neurons in the hidden layer have the number of inputs equal to the number of outputs from the previous layer. The number of output neurons of the network is the number of parameters that the ANNs will estimate. The output value of each neuron is calculated according to Equation (1) (Hagan et al. 2014).

$$a_j = w_0 + \sum_{i=1}^{n} x_i \times w_i \tag{1}$$

where:
a_j – output of neuron j;
n – number of inputs;
x_i, w_i – value and weight of input i;
w_0 – neuron bias.

In order to select the optimal hidden neurons, a trial-and-error procedure was considered. The number of hidden neurons started with one and increased up to 10 in each trial. To resolve the problem of overfitting, among the trained networks, the network with the lowest root mean square error (*RMSE*) on the validation set was selected as the optimum ANN model for each input combination (Kalteh 2017).

Several activation functions can be used on MLP network. In this study, the hyperbolic tangent, also known as the tan-sigmoid or tansig (Hagan et al. 2014), was used for the hidden layer neurons and the output layer neuron, see Equation (2).

$$\varphi_j(a_j) = \tanh(a_j) = \frac{2}{\left[1 + \exp(-2a_j)\right]} - 1 \tag{2}$$

where:
φ_j – output of the j^{th} node (neuron).

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Table 2. Height-diameter models selected for comparison

Model	Function	Model name
1	$h = 1.3 + a \times DBH^{b}$	Schreuder et al. (1979)
2	$h = 1.3 + \dfrac{a \times DBH}{b + DBH}$	Bates and Watts (1980)
3	$h = 1.3 + a \times \left[1 - \exp^{(-b \times DBH)}\right]$	Meyer (1940)
4	$h = 1.3 + a \times \exp^{\frac{b}{DBH}}$	Burkhart-Strub (1974)
5	$h = \dfrac{1.3 + DBH^{2}}{(a + b \times DBH)^{2}}$	Loetsch et al. (1973)
6	$h = 1.3 + \dfrac{a \times DBH}{(DBH + 1)} + (b \times DBH)$	Watts (1983)
7	$h = 1.3 + 10^{a} \times DBH^{b}$	Larson (1986)
8	$h = 1.3 + \dfrac{DBH^{2}}{a + b \times DBH + c \times DBH^{2}}$	Tomé (1988)
9	$h = 1.3 + a \times DBH^{b \times DBH^{-c}}$	Sibbesen (1981)
10	$h = 1.3 + a \times (1 - \exp^{-b \times DBH})^{c}$	Richards (1959)
11	$h = 1.3 + a \times (1 - \exp^{-b \times DBH})$	Yang et al. (1978)
12	$h = 1.3 + a \times \exp^{\frac{b}{(DBH + c)}}$	Ratkowsky (1990)
13	$h = 1.3 + \dfrac{DBH^{2}}{a + b \times DBH + c \times DBH^{2}}$	Prodan (1968)
14	$h = 1.3 + \exp\left[a + \left(b \times DBH^{c}\right)\right]$	Curtis (1981)
15	artificial neural network	ANN

a, *b*, *c* – model parameters to be estimated; *DBH* – diameter at breast height (cm); exp – the base of natural logarithm raised to a power of a number (exponent); *h* – total tree height (m)

Levenberg-Marquardt algorithm. The MLP training is divided into three stages: the propagation of input training patterns, error calculation and back-propagation of this error to adjust the weights of the neurons (Kalteh 2017). Several algorithms can be used to train the MLPs, the back-propagation training algorithm being the most popular one. But this algorithm poses several problems: it works at low speed, it needs a lot of off-line training, it exhibits temporal oscillations and it also tends to become

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stuck at local minima (Diamantopoulou et al. 2015). Therefore, we used the Levenberg-Marquardt learning algorithm. This algorithm is a refinement of the Gauss-Newton method, which is a variant of Newton's method. Newton's method uses information from the second-order partial derivative of the performance index used to adjust the weights. Thus, gradient information is used in conjunction with error surface curvature information. In a few words, Levenberg-Marquardt (LM) algorithm introduces the approximation to Hessian matrix (H_m) that is expressed in Equation (3), where J is the Jacobian matrix that contains the first derivatives of the network errors to the weights and biases, μ is the combination coefficient that is always positive and I is the identity matrix. The update rule of the LM algorithm is expressed by Equation (4), where w are the weights, and e are the biases. The effectiveness and convergence of the Levenberg-Marquardt artificial neural network (LMANN) models are very sensitive to the adjustment of the combination coefficient (μ) of Equation (3) (Hagan et al. 2014).

$$H_m = (J_i^T J_i + \mu_i I) \tag{3}$$

where:
H_m – Hessian matrix;
I – identity matrix;
J – Jacobian matrix;
μ – combination coefficient.

$$w_{i+1} = w_i - (H_m)^{-1} J_i^T e_i \tag{4}$$

where:
e – biases;
w – weights.

The measured data set was randomly divided into a fitting data set (70%) and an evaluation data set (30%) and then the data were normalized from –1 to 1 (Hagan et al. 2014). Diameter at breast height and height were used as input and output variables. Network training was performed by multilayer perceptron with LM algorithm in MATLAB software (Version 8.6, 2015) (Figure 2).

Model evaluation criteria. The data were fitted using nonlinear regression and the ordinary least-squares (OLS) technique. Four performance measuring criteria were used in this study: (*i*) root mean square error (*RMSE*) that provides information about

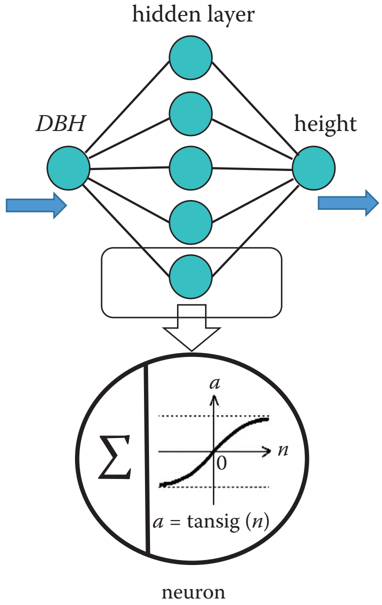

Figure 2. A three-layer perceptron

DBH – diameter at breast height

the short-term performance of a model by allowing a term-by-term comparison of the actual difference between the estimated and the measured value, the smaller the value, the better the model's performance; (*ii*) adjusted coefficient of determination (R^2_{adj}) that is a modified version of R^2 that has been adjusted for the number of predictors in the model (Sharma, Breidenbach 2015), the R^2_{adj} increases when the new term improves the model more than would be expected by chance; (*iii*) Akaike's information criterion (*AIC*) is a single number score that can be used to determine which of multiple models is most likely to be the best model for a given data set, it estimates models relatively, meaning that *AIC* scores are only useful in comparison with other *AIC* scores for the same data set, a lower *AIC* score is better (Burnham, Anderson 2004); (*iv*) mean absolute error (*MAE*) is a measure of errors between paired observations expressing the same phenomenon (Willmott, Matsuura 2005), see Equations (5–8).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(H_i - \hat{H}_i)^2}{n}} \tag{5}$$

where:
H_i – observed height;
$\hat{H}_i$ – estimated height by the models;
n – total number of data used for fitting the model;
$RMSE$ – root mean square error.

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$$R^2_{adj} = 1 - \frac{(n-1)\sum_{i=1}^{n}(H_i - \hat{H}_i)^2}{(n-p)\sum_{i=1}^{n}(H_i - \bar{H})^2} \quad (6)$$

where:
$\bar{H}$ – mean of estimated values;
p – number of model parameters;
R^2_{adj} – adjusted coefficient of determination.

$$AIC = n \times \ln(RMSE) + 2p \quad (7)$$

where:
AIC – Akaike's information criterion.

$$MAE = \frac{\sum_{i=1}^{n}\left|(H_i - \hat{H}_i)\right|}{n} \quad (8)$$

where:
MAE – mean absolute error.

Also, in order to examine the predictive ability of the models, 45-degree line plots were produced for all models (Diamantopoulou et al. 2015).

RESULTS

Model development. Before modelling the H-D models, the *DBH* and height distributions of beech were investigated based on each of the important topographic variables such as slope (less than 30%, 30–60%, and more than 60%) and elevation classes. The analysis of variance of diameter and height for beech based on slope classes in each region did not show any significant differences (Table 3).

Also, one sample *t*-test did not show significant differences between diameter and height in two altitude regions (Table 4).

Diameter and height relationship. The relationship of diameter and height of beech in both elevation classes was nonlinear (Figure 3) and based on mathematical functions it was a sigmoid type. According to these graphs, in high-altitude region for beech trees with a diameter less than 40 cm, the growth ratio of height to diameter is higher than for trees with a diameter greater than 40 cm. On the other hand, in the mid-altitude region this occurred at 60 cm (Figure 3).

Nonlinear model parameters. The OLS techniques were applied to estimate model fitting parameters for the model calibration dataset, see Table S1 in the Electronic Supplementary Material (ESM).

Optimum number of neurons in the artificial neural network. Among the trained ANN models, the model with the least *RMSE* in the testing set was chosen as the final optimum model. To decide on the optimum number of neurons in hidden layer, a trial-and-error approach was considered and number of neurons in the hidden layer was initially set from 1 to 10 neurons and each of them repeat-

Table 3. Analysis of variance for beech in slope classes

Region	Variable	Source	*SS*	*df*	*MS*	*F*	*P*-value
High-altitude	*DBH*	between groups	3 326.285	2	1 663.142	1.223	0.295[ns]
		within groups	1 990 972.649	1 464	1 359.954		
		total	1 994 298.934	1 466	–		
	height	between groups	187.551	2	93.775	0.990	0.372[ns]
		within groups	138 660.244	1 464	94.713		
		total	138 847.795	1 466	–		
Mid-altitude	*DBH*	between groups	2 237.594	2	1 118.797	1.060	0.347[ns]
		within groups	1 872 034.849	1 773	1 055.857		
		total	1 874 272.443	1 775	–		
	height	between groups	454.243	2	227.122	2.310	0.100[ns]
		within groups	174 341.902	1 773	98.332		
		total	174 796.146	1 775	–		

[ns] non-significant; *DBH* – diameter at breast height; *df* – degrees of freedom; *F* – Fisher's *F* ratio; *MS* – mean squares; *SS* – sum of squares

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Table 4. The t-test for beech in mid and high altitudes

Variables	t	df	Sig. (2-tailed)
DBH	63.710	3 242	0.001
Height	100.694	3 242	0.001

DBH – diameter at breast height; *df* – degrees of freedom; sig. – significant; t – Student's t-statistic

ed 100 times. Finally, the network with 5 neurons in the hidden layer posed the least *RMSE* in the testing set in two regions.

Model fitting and selection. The goodness of fit results and prediction accuracy of the high-altitude and mid-altitude regions for calibration and validation datasets are reported in Tables S2 and S3 in the ESM. In the high-altitude class, the R^2_{adj} ranged from 0.901 to 0.977 and the average was about 0.97. The *RMSE* ranged from 1.387 to 2.905 in the calibration dataset. The best *AIC* belongs to Model 14 and Model 3, and these two models also have the lowest *MAE* (Table S1 in the ESM). For the mid-altitude class, the R^2_{adj} ranged from 0.910 to 0.988 and the *RMSE* ranged from 1.289 to 3.447 in the calibration dataset. In this class, Model 2 had the best performance for *AIC* (139.22) and *MAE* (0.978), (Table S2 in the ESM).

High-altitude. The *RMSE* result revealed that the lowest value belongs to Model 3 with 1.387, Model 14 with 1.396, and Model 8 with 1.401 respectively (Table S1 in the ESM).

Mid-altitude. The *RMSE* results indicated that the lowest value belongs to Model 2 with 1.289, Model 13 with 1.315, and Model 8 with 1.316 respectively (Table S2 in the ESM).

The graphical technique revealed that the points in the chosen models did not lean in one direction and gathered around the identity line. In each of the two regions, the artificial neural network showed a better balanced fit than the selected non-linear models (Figure 4).

Inspecting the standard residual diagram against the estimated height indicated that the

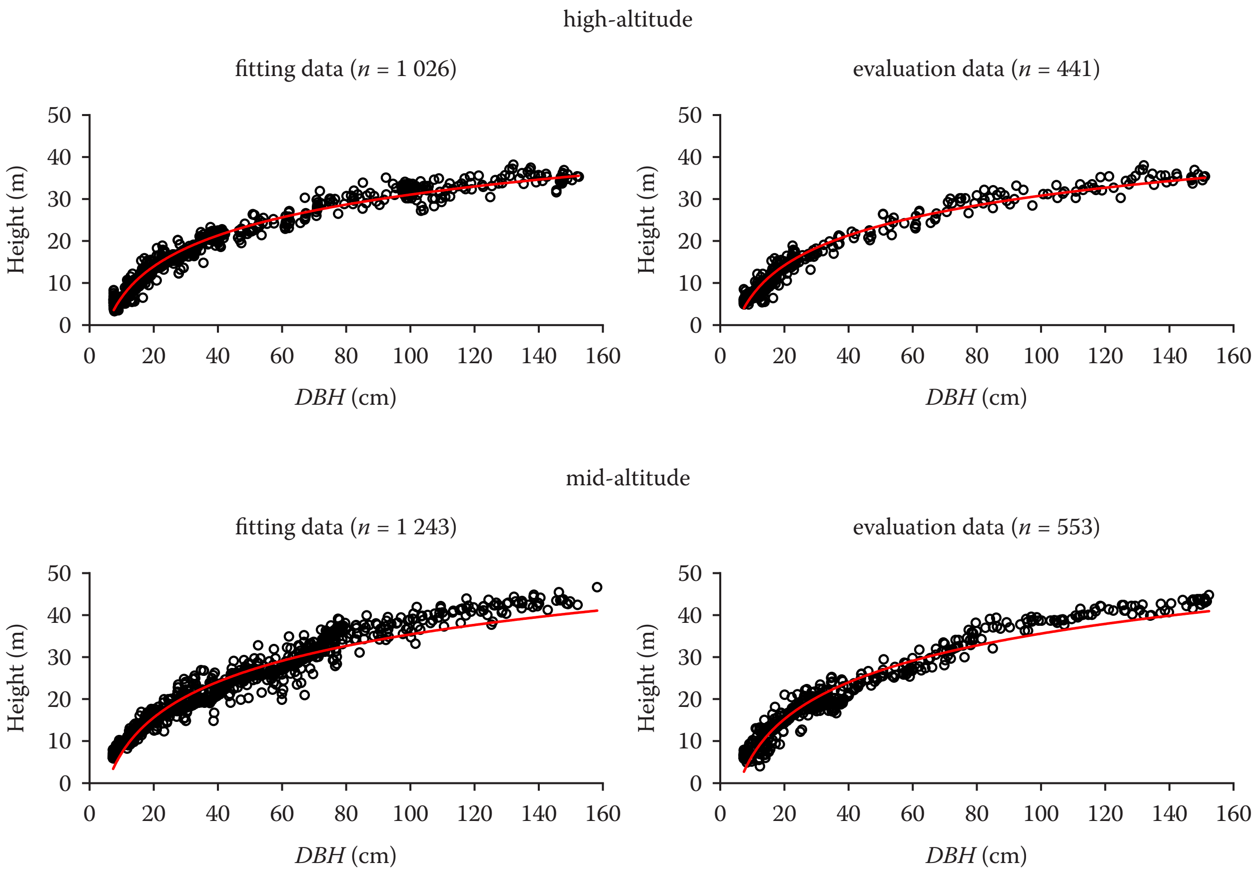

Figure 3. Height and diameter relationship of beech

DBH – diameter at breast height

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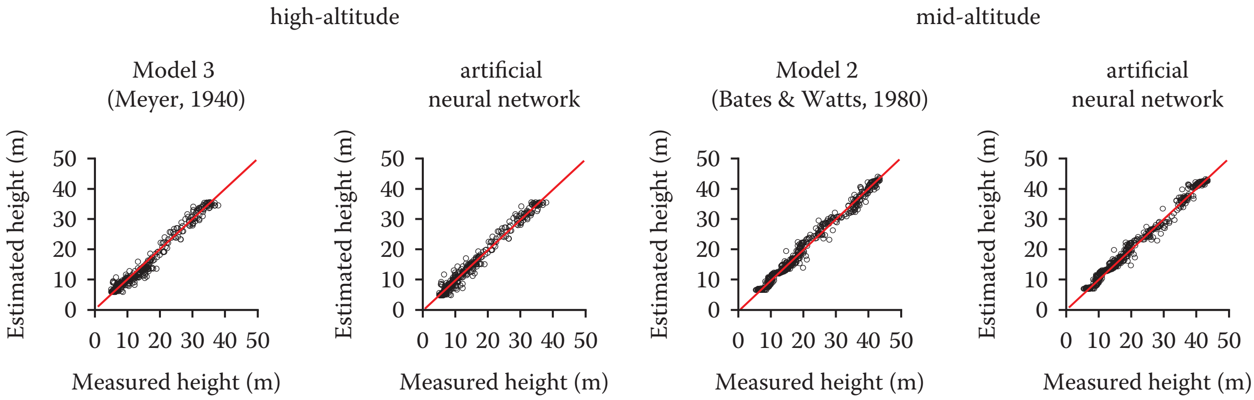

Figure 4. Measured height against estimated values

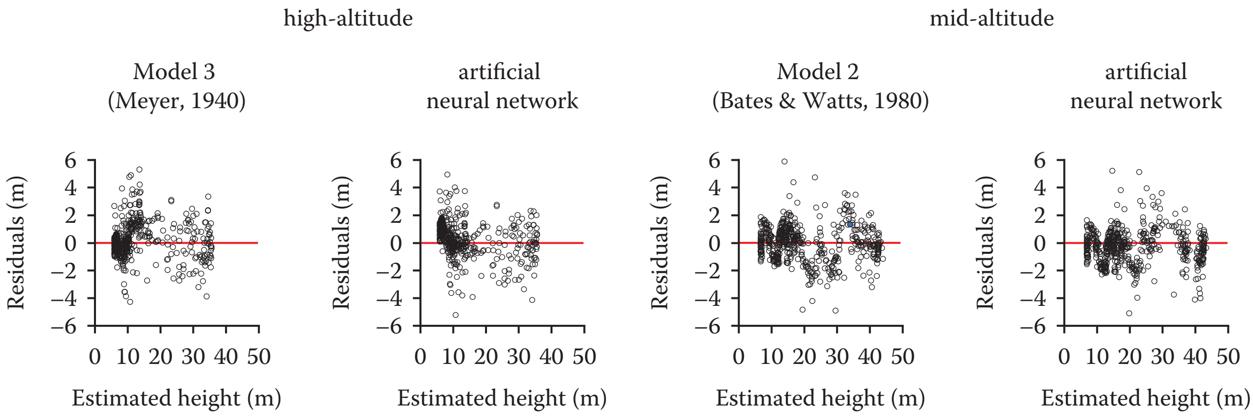

Figure 5. Residuals against estimated height for the best nonlinear models and ANNs

ANNs – artificial neural networks

ANN technique provided a more accurate estimate than the nonlinear models chosen (Ogana, Ercanli 2021; Figure 5).

DISCUSSION

Tree height is, along with the tree diameter, an essential variable in describing characteristics of forest stands (Sharma et al. 2018). Also, it is used in height to diameter ratio (*HDR*), known as slenderness coefficient, to evaluate the stability of trees and forest stands (Sharma et al. 2016b). The development of models such as H-D functions has been considered and replaced with the direct tree height measurement. Based on descriptive statistics, the diameter values for beech show differences in high-altitude and mid-altitude regions. However, in this study, there was only a minor difference between the values for high-altitude and mid-altitude regions: 152.5 and 158.5 cm, respectively (Mohammadi, Shataee 2018). However, it should be noted that beech diameter average in mid-altitude was higher than in the high-altitude region. The main reason is that the forest stand quality of mid-altitude is considerably better compared to the high-altitude region (Mugasha et al. 2019). This indicates that environmental conditions and geo-statistical variables, especially the altitude factor, would significantly impact changes in the growth of beech, as also found by Scaranello et al. (2012) and Králíček et al. (2017), where various models performed differently in different locations. Other reasons for this include the presence of diverse species, the vegetative nature of beech and variations in diameter and height development throughout vegetative periods, competition, and the many interactions of beech with these species (Ahmadi et al. 2013).

The assessment of H-D nonlinear models for beech in the two regions at the high-altitude and mid-altitude revealed that the efficiency of the nonlinear models to estimate the height of beech was very different (Nazari Sendi et al. 2020).

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An elite model has the smallest *RMSE* and the largest R^2_{adj}, which means that it outperforms the other models (Pham 2019). When some models have similar *RMSE* and R^2_{adj}, *AIC*, and *MAE* criteria play an important role to select the best model (Sanquetta et al. 2018). The Model 3 (Meyer 1940) had the highest accuracy in the high-altitude region, while in the mid-altitude, this model was one of the weaker models. One of the important points is that the best model for each species is appropriate to the type of species and related to their habitat conditions.

The results of this research validated earlier studies and findings that ANN model had better performance than nonlinear models. This model has the highest accuracy in estimating beech height rather than nonlinear models in both regions (Thanh et al. 2019). It had the lowest error rate compared to the best nonlinear H-D models, which was consistent with the results of Diamantopoulou et al. (2015). Thus, this approach is recommended in similar studies and to forest managers as a suitable and alternative method to the usual nonlinear models, which uses one factor as input and has good results regardless of environmental effects (Štefančík et al. 2018). The desired results can be achieved only by accurately measuring the diameter and selecting the appropriate model, while decreasing the costs, time, and error rate. In general, it can be stated that each growing area requires different planning for the management of forest stands (Nazari Sendi et al. 2014), especially in pure stands. Also, the use of nonlinear H-D models with the highest accuracy or ANN that can perform satisfactory estimation in habitats with different conditions is recommended to forest managers.

CONCLUSION

Due to geographical limitations, measuring tree height in natural forests takes a long time and makes it more expensive, thus the best approach is to use height-diameter models. The most important topographic factor is altitude, which has several effects on the distribution of species, as well as their quality and quantity. Beech is the main forest species in northern Iran, distributed mainly in the mountainous areas from the midland to the highlands. In this study, the height-diameter relationship for beech was based on altitude classes. Our findings indicated that nonlinear H-D models for beech in different stand characteristics, especially altitudes, are required to produce more accurate predictions of tree height. Also, the suitable models for the two classes of high-altitude and mid-altitude are completely different in terms of type and order. In using nonlinear H-D models, it should be noted how much the independent habitat variables (e.g. altitude and other environmental variables) affect the height estimated from tree diameter. Considering the importance of forest habitats in northern Iran, future research in this region and related environments should take this into consideration. In this regard, nonlinear models with mixed effects can be proposed and presented. It should also be emphasized that since the environmental conditions are different across various forest stands, to avoid errors and select the best model for a species, data integration should be avoided and the H-D model should be developed based on a diameter-height relationship investigated separately in each different habitat.

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