

Article

Estimation of Tree Heights in an Uneven-Aged, Mixed Forest in Northern Iran Using Artificial Intelligence and Empirical Models

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Abstract: The diameters and heights of trees are two of the most important components in a forest inventory. In some circumstances, the heights of trees need to be estimated due to the time and cost involved in measuring them in the field. Artificial intelligence models have many advantages in modeling nonlinear height–diameter relationships of trees, which sometimes make them more useful than empirical models in estimating the heights of trees. In the present study, the heights of trees in uneven-aged and mixed stands in the high elevation forests of northern Iran were estimated using an artificial neural network (ANN) model, an adaptive neuro-fuzzy inference system (ANFIS) model, and empirical models. A systematic sampling method with a 150 × 200 m network (0.1 ha area) was employed. The diameters and heights of 516 trees were measured to support the modeling effort. Using 10 nonlinear empirical models, the ANN model, and the ANFIS model, the relationship between height as a dependent variable and diameter as an independent variable was analyzed. The results show, according to R^2 , relative root mean square error (RMSE), and other model evaluation criteria, that there is a greater consistency between predicted height and observed height when using artificial intelligence models ($R^2 = 0.78$; RMSE (%) = 18.49) than when using regression analysis ($R^2 = 0.68$; RMSE (%) = 17.69). Thus, it can be said that these models may be better than empirical models for predicting the heights of common, commercially-important trees in the study area.

Keywords: total tree height; diameter at breast height; diameter-height model; ANN; ANFIS; nonlinear regression

1. Introduction

Hyrcanian forests, the only commercial forests in Iran, are considered complete biological communities. They have the highest degree of self-regulation and self-renewal among all natural ecosystems in Iran. Hyrcanian forests can be considered both as a starting point for efforts to maintain

an ecological balance in nature, and as a model of irreplaceable pattern in forest science for the application of different methods of forestry [1–3]. In concert with new management approaches for forest ecosystems, which can be based on multipurpose forestry goals, managers need accurate and precise diameter–height relationships to assess growth and production in the sustainable management of these resources [4,5]. Hence, diameter–height models are essential to better understand different relationships in nature, as well as to describe and study the differences and effects on forest ecosystem development [4,6,7]. Further, the accuracy of such models is very important for the preparation of accurate volume tables and for the development of growth prediction models [8]. For this reason, forest managers need to be informed of the connection between the diameters and heights of trees, and be able to accurately estimate the heights of trees using diameter at breast height (DBH). Oriental beech (*Fagus orientalis* Lipsky), commonhornbeam (*Carpinus betulus* L.), Caucasian alder (*Alnus subcordata* C.A. Mey), velvetmaple (*Acer velutinum* Boiss.), and large-leaved lime tree (*Tilia platyphyllos* Scop.) are the main native species of the northern Hyrcanian forests of Iran, and are the most important and most valuable commercial species. Studying the height and diameter characteristics of these trees is very important and can provide valuable information for the management of these forests by future generations of society.

Total tree height is an important factor in forest management, as it is needed for determining many important forest-related indexes, such as growing stock volume, above-ground biomass, and carbon stock [9]. While total tree height can be directly measured with analog devices (clinometers) or lasers, there are several methods for estimating total tree height, and they fall into three common categories: empirical, process, and hybrid models. Biological factors such as age and diameter are the main inputs of empirical regression models to estimate tree height [10]. Process models can be created by including local indicators, such as precipitation, climate, and soil properties of the area, and other relevant factors to estimate total tree height. Hybrid models to estimate tree heights, through the integration of experimental models and process models, can also be created. These include mixed linear effects models and nonlinear mixed effects models, which may increase both accuracy and flexibility in modeling total tree height [11].

The use of artificial intelligence (AI) methods to estimate forest yield has been highlighted in recent years. Artificial neural networks (ANNs) are a group of AI methods that can be used as an alternative to traditional modeling techniques such as regression models [12], because they are more generalizable, and are less sensitive to noise and outliers. They can be more powerful than regression models when modeling nonlinear relationships unknown to modelers [13]. Importantly, the implementation of AI techniques in forestry has generally been limited to the use of ANNs and other similar methods, such as fuzzy logic and adaptive neuro-fuzzy inference systems (ANFIS). Results of different studies have illustrated satisfactory results for the prediction of landslides, wildfires, and forest road network suitability [14–16]. However, the use of ANNs to address nonlinear growth and yield problems has also become a very important issue [17]. These types of models are able to address problems with nonlinear relationships between model parameters, and they are not restricted by the assumptions of empirical models [8,18]. An ANFIS is a fuzzy system with a parallel structure, and neural network learning algorithms are used to adjust the fuzzy system parameters [13]. Although the use of ANFIS in many fields still is in early stages, in recent years good results have been realized when applying these methods to some forestry problems [19–21].

Different models of height and diameter relationships have been presented in the literature. For example, Özçelik et al. [8] modeled height–diameter relationships in southwestern Turkey using empirical models and neural networks. Their results showed that neural network models may be a good alternative to other methods for estimating tree heights. Ahmadi et al. [22] modeled height–diameter relationships in the educational and research forest of Tarbiat Modares University using Weibull, Schnute, and Richards forms of regression, and found that Richards’ model performed the best due to its greater efficiency. Bayat et al. [23] used diameter and height models to obtain the height of *Fagus orientalis* in the Gorazbon district of the Kheiroud educational research forest of

Iran, and showed that the Prodan model had more acceptable results than others examined. Vieira et al. [13] used empirical models, ANNs, and ANFIS models to obtain the diameters and heights of trees of eucalyptus. They concluded that the ANN and the ANFIS models had greater accuracy than empirical models in diameter and height estimation. Nguyen Thanh et al. [24] examined the usefulness of nonlinear equations and ANN models for describing height–diameter relationships in three diverse stand densities of a Korean pine plantation, and found that while all models performed well in describing height–diameter relationships, ANN models could decrease the RMSE the greatest. Zhou et al. [11] estimated DBH in a forest area in China using multivariate linear regression and generalized regression neural network models, and found that the latter provided better results with stronger generalizability.

Generally, the above studies on the effectiveness of different height–diameter models indicated that results can vary for different habitats and species, and even in different conditions, such as different stand densities and relative positions of trees. The purpose of this paper is to examine the quality of results produced by estimating total tree height from DBH in Hyrcanian forests, using ANN and ANFIS models, so that the advantages and disadvantages of these methods can be compared against more traditional empirical models. Further, we hope to find an accurate and appropriate method for predicting tree heights for the most important and economically valuable species in the forests of northern Iran.

2. Materials and Methods

2.1. Study Area

The study was conducted in Kheyroud forest, which is an experimental forest located in an 80 km², unmanaged section of the greater Hyrcanian forests in Mazandaran province in northern Iran (Figure 1). Kheyroud forest is located the 7 km east of Noshahr at 36°39' N, 51°30' E; datum WGS84. This forest has eight sections, one of which is the Gorazbon section [3]. These areas support about 80 native tree species and 50 native shrub species. The mean annual precipitation, temperature, and evaporation in this area are 1.397 mm, 15.5 °C, and 1.031 mm, respectively. The highest elevation for the Gorazbon section is reported to be 1380 m AMSL and the lower northern boundary is located at about 1010 m AMSL. This area is also karst in character, and Calcisols are the main types of soils [23].

The Gorazbon section of Kheyroud is composed of an uneven-aged, mixed species forest, and in most parts has at least three stories. The main species of this section are oriental beech, common hornbeam, Caucasian alder, and Persian maple. In addition, due to the prevailing ecological conditions in this section, oak, hornbeam, maple, alder, lily, and barangay forest stands have been introduced into the beech communities. In general, four forest vegetation communities were identified in the Gorazbon section: (1) a *Quercus-Carpinetum* community, (2) a *Fageto-Carpinetum* community, (3) a *Fagetum* mix community, and (4) a *Fagetum orientalis* community. This forest is in the range of 0.5 to 1.5 for biodiversity indices such as the Shannon–Wiener index and the Simpson index [3].

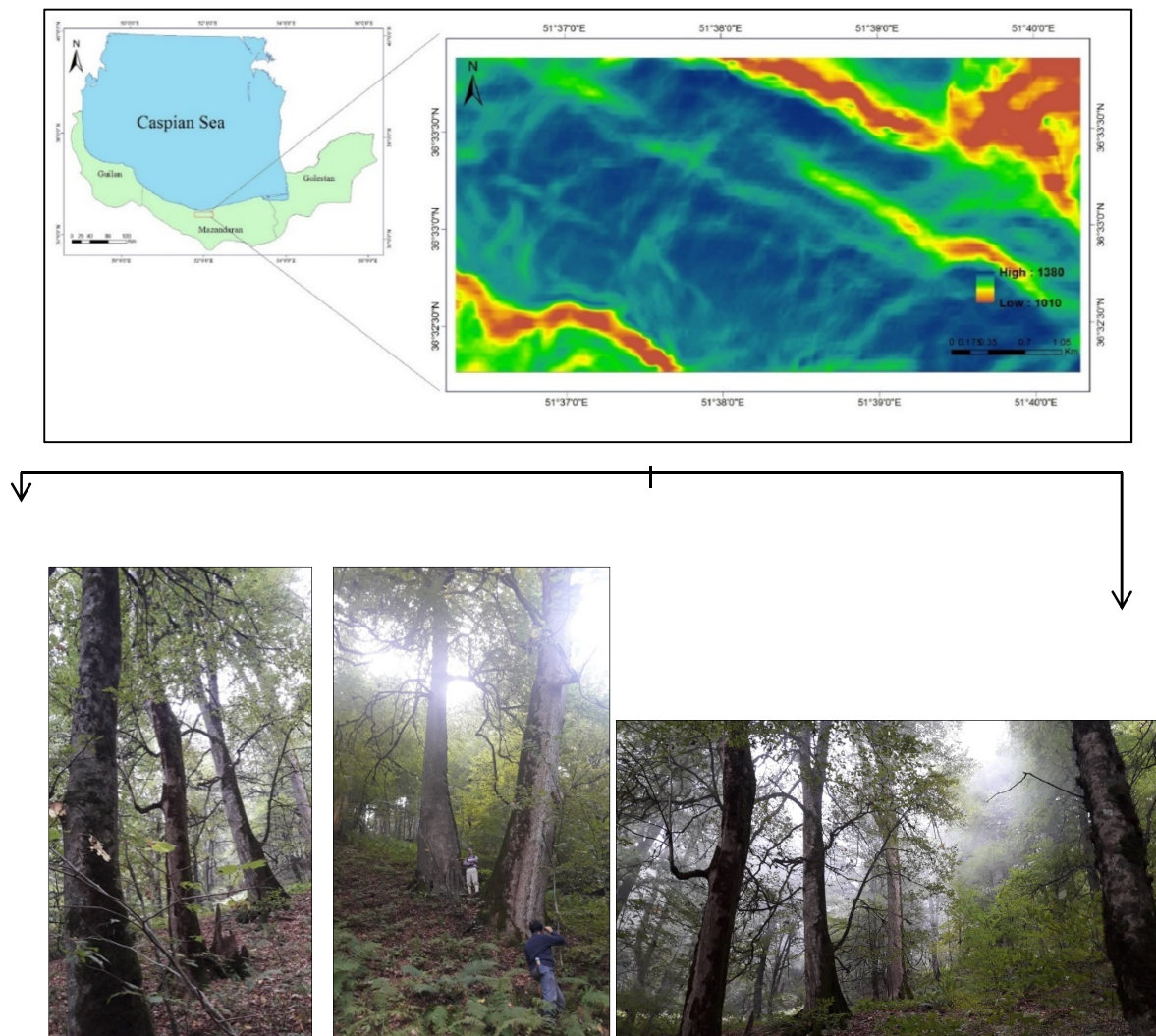


Figure 1. Location and example conditions of the study area.

2.2. Data Collection

The data collection effort was carried out in a systematic manner, by distributing 258 0.1-hectare fixed circular plots on a rectangular grid of 150×200 m throughout the study area. The DBHs of the trees before and after the growing season were measured in 2003 and 2012. In 2012, new trees (ingrowth), that were 8 cm or greater in diameter were added to the inventory, and their characteristics were recorded. The analysis of this study is partly based on data collected in 2003 and the mixed effect was not significant. The workflow associated with this project is illustrated in Figure 2.

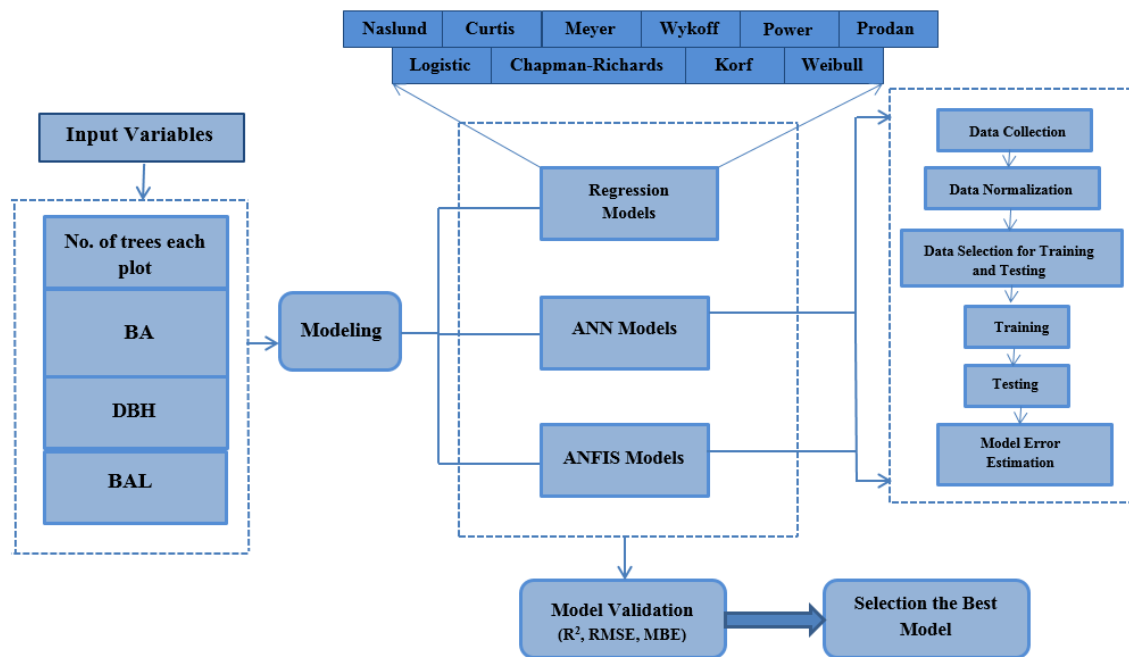


Figure 2. The workflow employed in this study to quantify the tree heights using artificial intelligence and empirical models. BA: basal Area (m^2ha^{-1}), DBH: diameter at breast height (cm), BAL: basal area in the largest tree (m^2ha^{-1}).

2.3. The Tree Database

The diameters and heights of the largest (with respect to DBH according to [2]) trees closest to the center of each circular sample plot were measured. Diameters were measured using calipers, and as a result, 516 paired DBH and total tree height data points were available for the subsequent modeling efforts. For purposes of this study, 70% of the data (height-DBH pairs) was used for modeling and the remaining 30% was used for evaluating the resulting models. For 10 nonlinear empirical models, the relationship between total height (the dependent variable) and DBH (the independent variable) was considered and analyzed using R software. These measurements suggest that a high degree of variability exists in the tree density and the average size of trees (Table 1). The means, minima, maxima, and standard deviations of the diameter at the breast height and the height, respectively, of all trees in the study area, are shown in Table 1. There were wide ranges in diameters and heights of the sample trees, and therefore, there was a relatively high amount of variation in the data. The coefficient of variation in DBH measurements was over 52%, while the coefficient of variation in total tree height measurements was over 31%.

Table 1. Statistical characteristics of the diameter at breast height (DBH) and total height measurements of trees.

Descriptive Statistics	Diameter at Breast Height (cm)			Height (m)		
	Training	Testing	All	Training	Testing	All
Mean	69.11	71.56	69.99	29.21	31.65	30.09
Minimum	8	8	8	7.4	7.5	7.4
Maximum	188	172	188	50	50.5	50.5
Standard deviation	39.23	37.54	38.62	9.26	10.28	9.69

2.4. Input Variables of the Models

The variables used for predicting the heights of trees in this study were diameter at breast height (DBH, cm), basal area of the largest trees (BAL, m^2ha^{-1}), total basal area (BA, m^2ha^{-1}), and number of

trees in each plot (NT). In our study, no site factors were included in any of the models. In initial tests, slope, elevation, and aspect were found to not be significant predictors of tree heights, most probably because the data were collected from a limited area [2].

2.5. Artificial Neural Network (ANN) Models

ANNs are widely used machine learning methods, and are inspired by the human brain's nervous system and the massive set of parallel processing units, functioning as a collective system, which solves problems [25]. These models, like other artificial intelligence methods, can simplify complex, nonlinear relationships among phenomena. Multi-layer perceptron is a class of ANN that was used in this study because it has high efficiency when solving classification problems. A multi-layer perceptron ANN consists of neurons that contain input, hidden, and output layers that act in concert to converge on a minimum-error solution to a problem [25,26]. A feed-forward back-propagation algorithm is also used for regulating the relationship between neurosis and weights (W_i). Another algorithm employed which is commonly used in natural resource studies ([27,28] and references therein) is back propagation, in which a matrix of weights creates connections between neurons. The net input of each neuron (x_i) is a function of an assumed weight matrix [18].

2.6. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is based on fuzzy logic and adheres to ANN principles to deal with the nonlinear functions and address turbulent time series data [29]. An ANFIS is thus an intelligent system derived from two important components (ANN and fuzzy logic), and is widely used in natural hazard prediction (e.g., [13] and references therein). Structurally, the ANFIS model has a layered network that includes an input layer of three neurons, a fuzzy layer with six membership functions, one layer with 9 fuzzy rules, a normalization layer with 9 neurons, and one final layer with a single neuron [19]. The full details of the ANFIS model can be found in related literature [29,30].

Input data for training and testing are required for each network. In the present study, 70% of data were for network training, 15% for validation, and 15% for testing purposes.

$$net = \sum_{i=1}^n W_i x_i + \theta \quad (1)$$

where, W_i is the weight and x_i is the input; θ represents the bias weights; and net is the output of each neuron that is determined by the sigmoid transfer function (Equation (2)), which is the most common activation function in a back propagation training algorithm.

$$f(net) = \frac{1}{1 + \exp(-net)} \quad (2)$$

The details of the neural network method, including input, output, and activation functions, can be seen in Table 2.

Table 2. Descriptions of ANN and ANFIS with their activation functions and input and output variables for estimating total height.

	Model	Input Variable	Network Topology	Output
ANN	ANN1	BAL, DBH, BA, NT	Log-sigmoid	TH
	ANN2	BAL, DBH, BA, NT	Hyperbolic tangent sigmoid	TH
	ANN3	BAL, DBH, BA	Log-sigmoid	TH
ANFIS	ANFIS1	BAL, DBH, BA, NT	Subtractive clustering	TH
	ANFIS2	BAL, DBH, BA, NT	Grid partition	TH
	ANFIS3	BAL, DBH, BA	Subtractive clustering	TH

BAL: basal area of the largest trees (m^2ha^{-1}), TH: total height (m), DBH: diameter at breast height (cm), BA: total basal area (m^2ha^{-1}), and NT: number of trees per plot.

The log-sigmoid activation function is:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

where x is input information of neuron and $f(x)$ is an activation function whose result ranges between 0 and 1 [31]. A hyperbolic tangent sigmoid function is related to a bipolar sigmoid function whose outputs range from -1 to 1 [32]. Subtractive clustering (SC) is an upgraded version of the mountain method, which depends heavily on data dimensions and network resolution, so it is not efficient for high-dimensional and high-resolution datasets [33]. The grid partition algorithm is limited to a few partition entries, because the number of rules increases exponentially with an increasing number of entries, causing difficulty in processing [34].

2.7. Performance Evaluation

To evaluate the quality of the method used, the indicators described in the Table 3 are assessed. In order to understand the relationship between the observed values and the modeled values, diagrams have been plotted, along with diagrams to visualize the residuals. The errors of observations are also expressed in percentages (Equation (3)).

Table 3. Statistical indexes used to evaluate the efficiencies of the models.

Statistical Indicators	Equation
Coefficient of determination	$R^2(\%) = \frac{\sum (y_i - \bar{y}) \times (\hat{y}_i - \bar{\hat{y}})}{\sqrt{[\sum_{i=1}^n (y_i - \bar{y})^2] \times [\sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2]}} \cdot 100$
Relative mean bias error	$MBE(\%) = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{n} \times \frac{100}{\bar{y}}$
Relative mean absolute error	$MAE(\%) = \frac{\sum_{i=1}^n y_i - \hat{y}_i }{n} \times \frac{100}{\bar{y}}$
Relative root mean square error	$RMSE(\%) = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \times \frac{100}{\bar{y}}$

Wherein: y_i : observed value of the i th variable; $\hat{y}_i$: estimated value of the i th variable; $\bar{y}$: mean of the observed values of the variable; $\bar{\hat{y}}$: mean of the estimated values of the variable; n : sample size

$$E(\%) = \frac{y_i - \hat{y}_i}{y_i} \times 100 \quad (4)$$

where: $E(\%)$ = error of each observation; y_i : observed value of the i th variable; $\hat{y}_i$: modeled value of the i th variable.

2.8. Estimation of Parameters and Comparison of Empirical Models

Traditional empirical prediction models examine the relationship between one or more independent variable (e.g., tree diameter, canopy width) and a dependent variable (e.g., tree height) for circumstances in which the cost of collecting the dependent variable data is very high. In this paper, 10 empirical diameter-height models were developed to predict the heights of trees in the study area (Table 4). These nonlinear empirical models included five models with two parameters, and five models with three parameters. The relationship between total tree height (the dependent variable) and DBH (the independent variable) was examined and analyzed using R software.

Table 4. Nonlinear empirical diameter and height models.

Number	Model	Algebraic Phrase	Reference
1	Naslund	$H = 1.3 + \frac{D^2}{(aD+b)^2}$	[35,36]
2	Curtis	$H = 1.3 + \frac{aD}{(1+D)^b}$	[37]
3	Meyer	$H = 1.3 + a(1 - \exp(-bD))$	[37,38]
4	Power	$H = 1.3 + aD^b$	[39]
5	Wykoff	$H = 1.3 + \exp(a - b(D+1)^{-1})$	[40]
6	Prodan	$H = 1.3 + \frac{D^2}{aD^2+bD+c}$	[37,41]
7	Logistic	$H = 1.3 + (\frac{a}{1+b \exp(-cD)})$	[42,43]
8	Chapman-Richards	$H = 1.3 + a(1 - \exp(-bD))^c$	[43,44]
9	Weibull	$H = 1.3 + a(1 - \exp(-bD^c))$	[43,45]
10	Korf	$H = 1.3 + a \exp(-bD^{-c})$	[46–48]

H: tree height; D: tree diameter at breast height; a, b, c: parameters of models.

3. Results

3.1. Modeling and Prediction Based on Empirical Models

The coefficients of the empirical models are noted in Table 5; the modeling results indicate that the variation in the independent variable (DBH) described is about 64%–69% of the variation in total tree height. This reflects the development of moderately good models; however, the RMSE is quite large (18%–24%) for each model. According to the results, the Weibull model, with an R^2 of 0.6875, an RMSE(%) of 18.28, and a BIAS of 1.28, seemed to be best able to estimate tree heights, even though the Curtis model had the lowest bias. When the models developed were applied to the evaluation data, the Weibull model also seemed to perform the best, as it had the highest R^2 and lowest RMSE, even though the Curtis model once again had the lowest bias (Table 6). Figures 3 and 4 illustrate the behaviors of the two and three-parametric models for estimating tree height based on DBH, and Figure 5 shows the behavior of the best model. Figure 6 shows the predicted height values against the actual heights obtained in the empirical models. The distributions of observed vs. estimated tree heights suggest that the power or the Weibull empirical models more reasonably estimate total tree heights from DBH measurements. The other eight models all displayed some problems in estimating either the maximum (seven of the models) or the minimum (the logistic model) total tree height. In summary, from this analysis, the Weibull model was selected as the best model among the 10 empirical models.

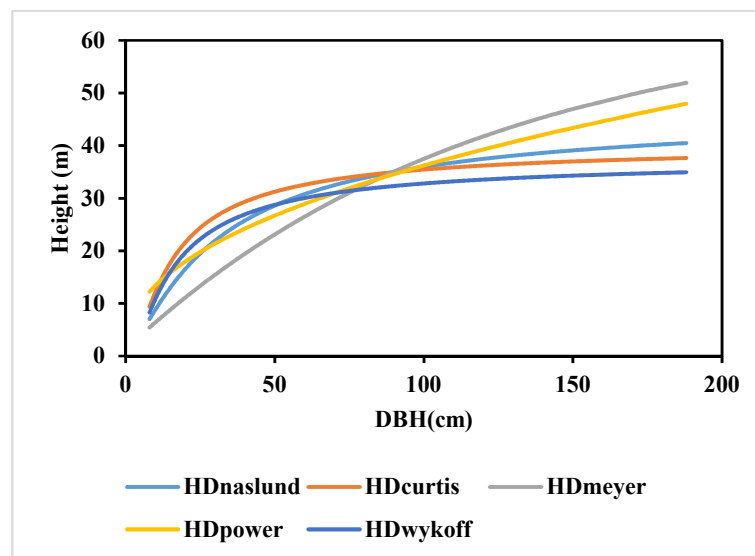
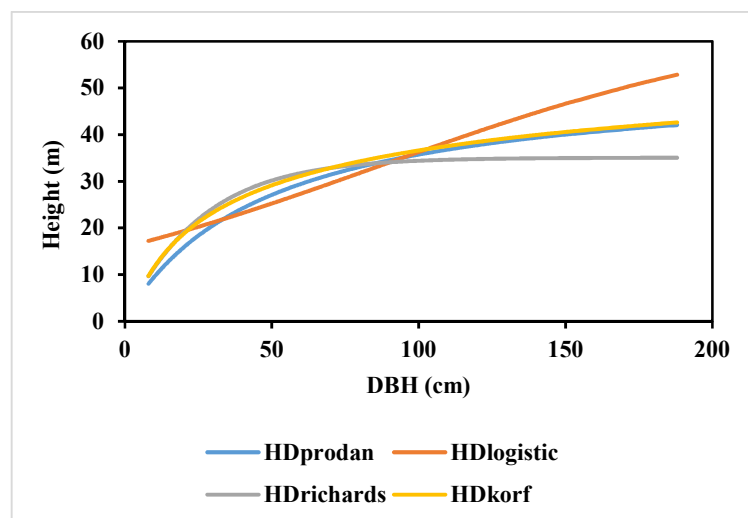
Table 5. Regression coefficients of models developed in this study.

Number	Model	Algebraic Phrase	Coefficients of Models		
			a	b	C
1	Naslund	$H = 1.3 + \frac{D^2}{(aD+b)^2}$	2.15	0.14	-
2	Curtis	$H = 1.3 + \frac{aD}{(1+D)^b}$	39.00	13.37	-
3	Meyer	$H = 1.3 + a(1 - \exp(-bD))$	63.96	0.008	-
4	Power	$H = 1.3 + aD^b$	4.21	0.42	-
5	Wykoff	$H = 1.3 + \exp(a - b(D+1)^{-1})$	3.62	-13.59	-
6	Prodan	$H = 1.3 + \frac{D^2}{aD^2+bD+c}$	0.64	0.95	0.019
7	Logistic	$H = 1.3 + (\frac{a}{1+b \exp(-cD)})$	63.96	3.37	0.014
8	Chapman-Richards	$H = 1.3 + a(1 - \exp(-bD))^c$	33.77	0.04	1.078
9	Weibull	$H = 1.3 + a(1 - \exp(-bD^c))$	63.96	0.051	0.59
10	Korf	$H = 1.3 + a \exp(-bD^{-c})$	63.96	5.56	0.48

Table 6. Coefficient of determination, RMSE, and MAE for modeling and validation of 10 nonlinear models.

Number	Model	Training				Testing			
		R^2	RMSE (%)	% MBA	% MAE	R^2	RMSE (%)	% MBA	% MAE
1	Naslund	0.68	18.86	3.31	16.18	0.68	18.79	2.97	14.15
2	Curtis	0.67	20.33	1.75	16.55	0.67	19.14	2.37	15.17
3	Meyer	0.64	24.16	8.94	20.41	0.64	22.74	4.82	18.28
4	Power	0.68	18.44	2.37	15.7	0.67	18.19	2.36	13.89
5	Wykoff	0.67	20.29	6.26	17.18	0.67	21.80	4.55	16.08
6	Prodan	0.67	18.99	5.21	16.32	0.67	19.17	3.85	14.23
7	Logistic	0.67	19.57	1.56	16.43	0.67	19.20	1.78	15.39
8	Chapman-Richards	0.68	19.88	2.62	16.54	0.68	20.12	2.99	15.18
9	Weibull	0.68	18.27	0.24	15.50	0.68	17.69	1.126	13.50
10	Korf	0.68	18.75	1.529	15.584	0.68	17.94	1.484	13.71

The best models based on R^2 and %RMSE are highlighted.

**Figure 3.** Diameter-predicted heights of the two-parameter models.**Figure 4.** Diameter-predicted heights of the three-parameter models.

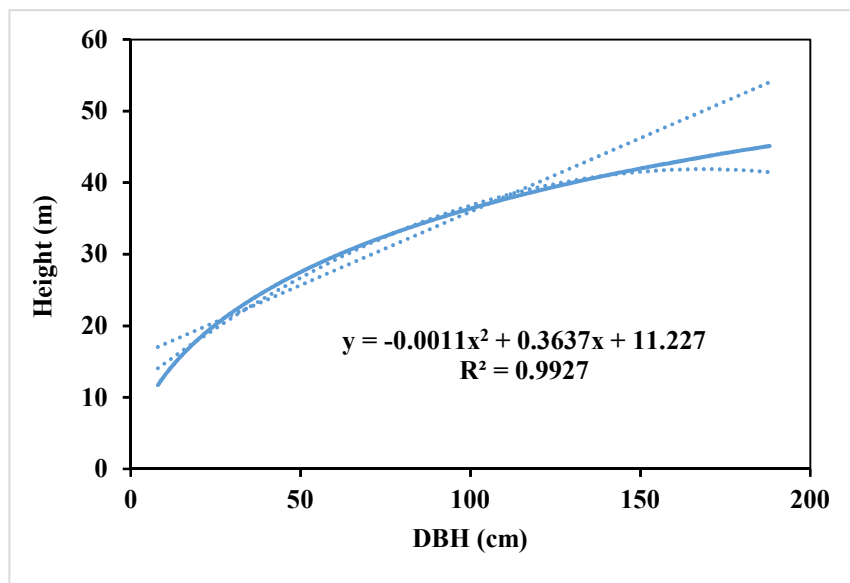


Figure 5. Diameter-predicted heights of the selected model (Weibull).

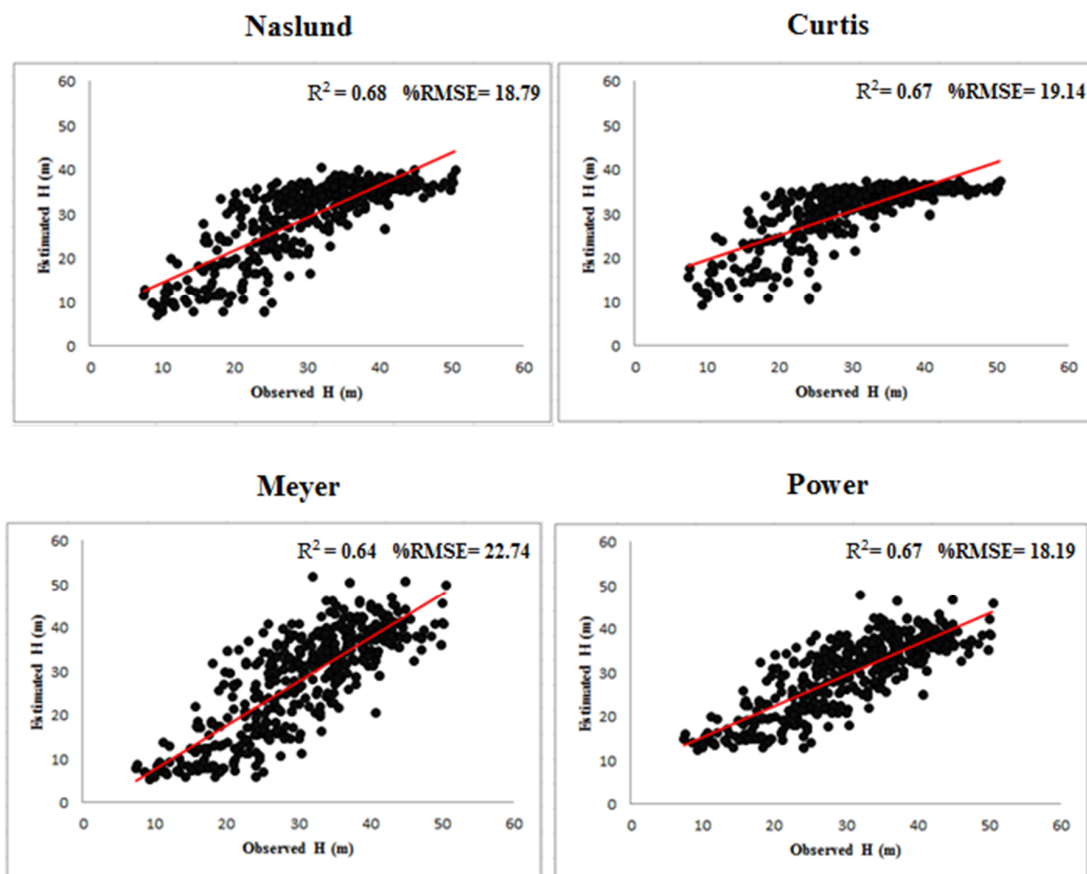


Figure 6. Cont.

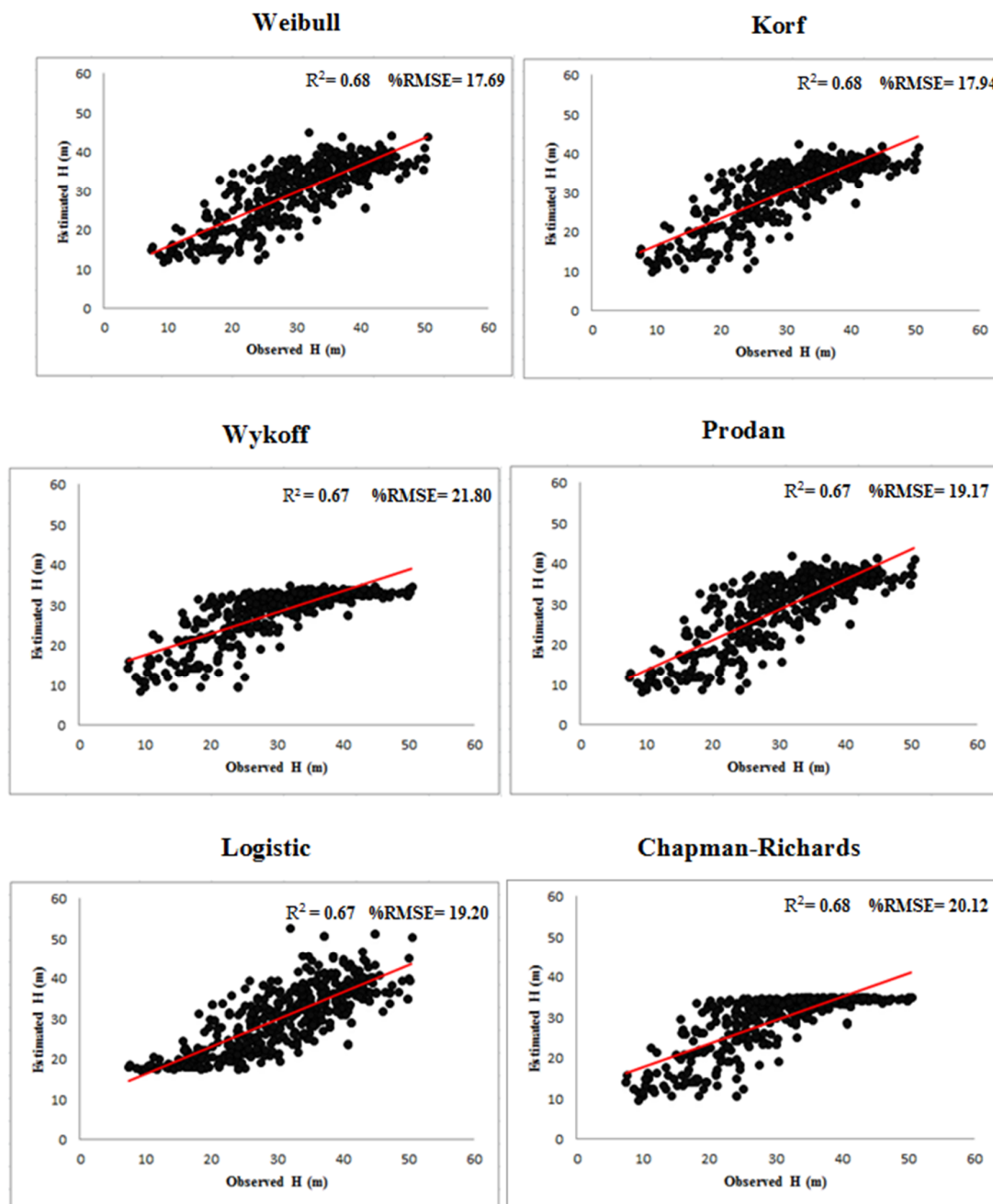


Figure 6. Estimated heights versus observed heights by 10 empirical models (testing R^2 and RMSE (%) noted).

3.2. Modeling and Prediction Based on ANN and ANFIS Models

As can be seen in the Table 7, most of the parameters for validation using ANN and ANFIS models are very similar. Table 8 illustrates outcomes from the results of training and validation efficiency using the ANN and ANFIS models. In Figures 7 and 8, the correlation between the observed and predicted height values, and the error rates of ANN and ANFIS models, are shown. The distribution among the estimated and observed total tree heights is reasonable, and does not display the problems noted earlier (related to maximum or minimum heights) with eight of the empirical models. Table 8 compares RMSE% and R^2 between all three groups of models (empirical models, ANFIS and ANN). As it can be seen, the R^2 is clearly higher when using the artificial intelligence models than the empirical models, and the RMSE is either similar or smaller than what was observed with the ten empirical models.

Table 7. Training, validation, and test statistics for the estimation of total height using ANN and ANFIS models.

ANN					
Model		R^2 (%)	MBE (%)	MAE (%)	RMSE (%)
1	Training	86.01	−0.96	13.98	16.89
	Validation	81.54	1.68	16.74	20.05
	Test	78.06	−5.74	14.99	18.52
2	Training	86.08	−0.98	13.60	17.00
	Validation	81.69	1.50	16.48	20.11
	Test	78.73	−5.63	14.93	18.49
3	Training	85.22	−0.90	14.02	17.04
	Validation	80.09	1.75	16.87	20.17
	Test	76.13	−4.55	15.36	18.97
ANFIS					
1	Training	86.15	0.00	13.38	16.91
	Validation	84.35	3.11	15.89	18.97
	Test	78.69	−5.97	14.66	18.62
2	Training	86.12	0.13	13.45	17.04
	Validation	84.20	3.18	15.93	19.09
	Test	77.97	−5.99	14.89	18.96
3	Training	85.87	0.16	13.54	17.11
	Validation	84.11	3.32	15.99	19.18
	Test	77.78	−6.08	14.97	18.99

The best models based on R^2 and %RMSE are highlighted.

Table 8. Validation results of the regression, ANN, and ANFIS models.

Model		RMSE (%)	R^2
Regression	Naslund	18.79	0.68
	Curtis	19.14	0.67
	Meyer	22.74	0.64
	Power	18.19	0.67
	Wykoff	21.80	0.67
	Prodan	19.17	0.67
	Logistic	19.20	0.67
	Chapman Richards	20.12	0.68
	Weibull	17.69	0.68
	Korf	17.94	0.68
ANN1	Training	17.00	16.89
	Validation	20.11	20.05
	Test	18.49	18.52
ANN2	Training	86.01	17.00
	Validation	81.54	20.11
	Test	78.06	18.49
ANN3	Training	86.08	17.04
	Validation	81.69	20.17
	Test	78.73	18.97
ANFIS1	Training	86.15	16.91
	Validation	84.35	18.97
	Test	78.69	18.62
ANFIS2	Training	86.12	17.04
	Validation	84.20	19.09
	Test	77.97	18.96
ANFIS3	Training	85.87	17.11
	Validation	84.11	19.18
	Test	77.78	18.99

The best models based on R^2 and %RMSE are highlighted.

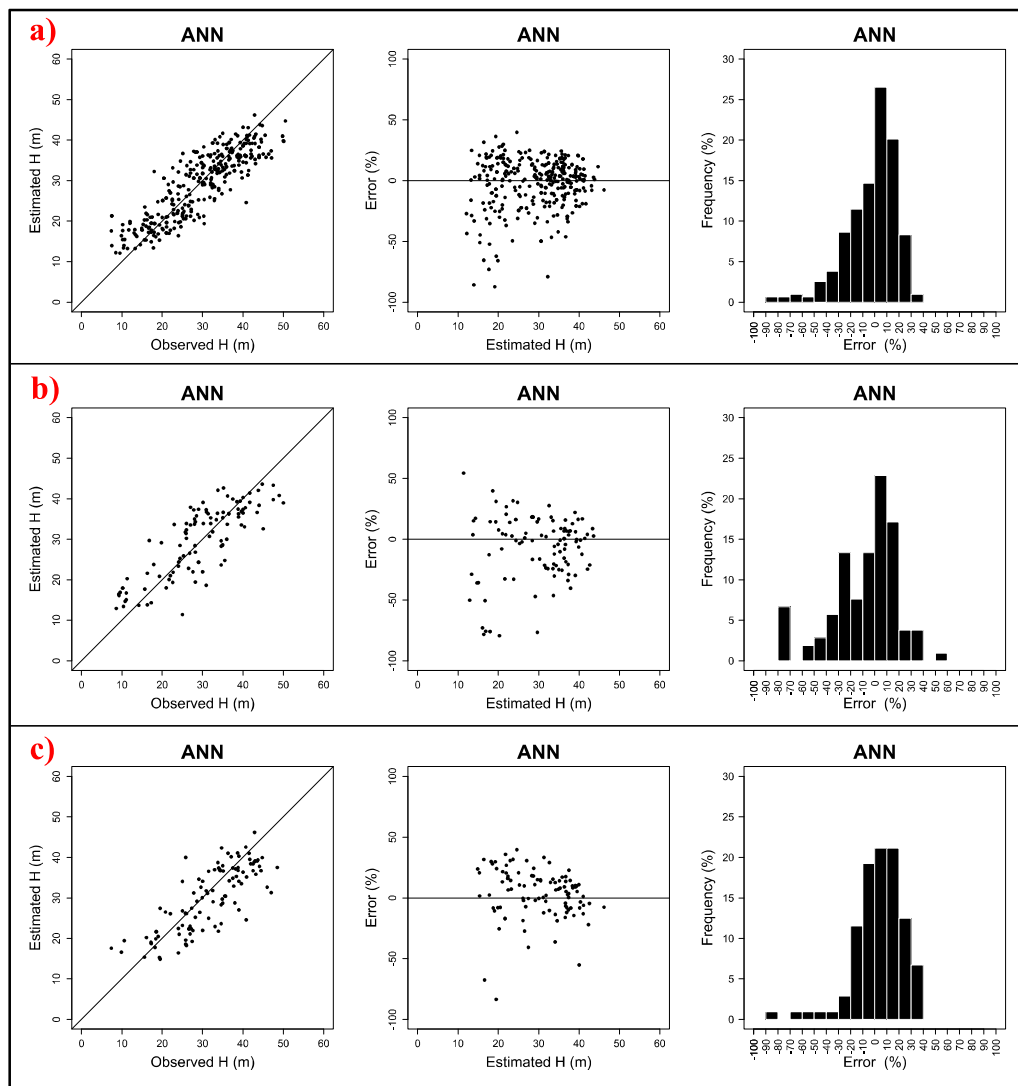


Figure 7. Estimated heights versus observed heights, distributions of percentage errors of height estimates, and histograms of errors of height estimates, obtained by ANN, for training (a), validation (b), and test (c) data.

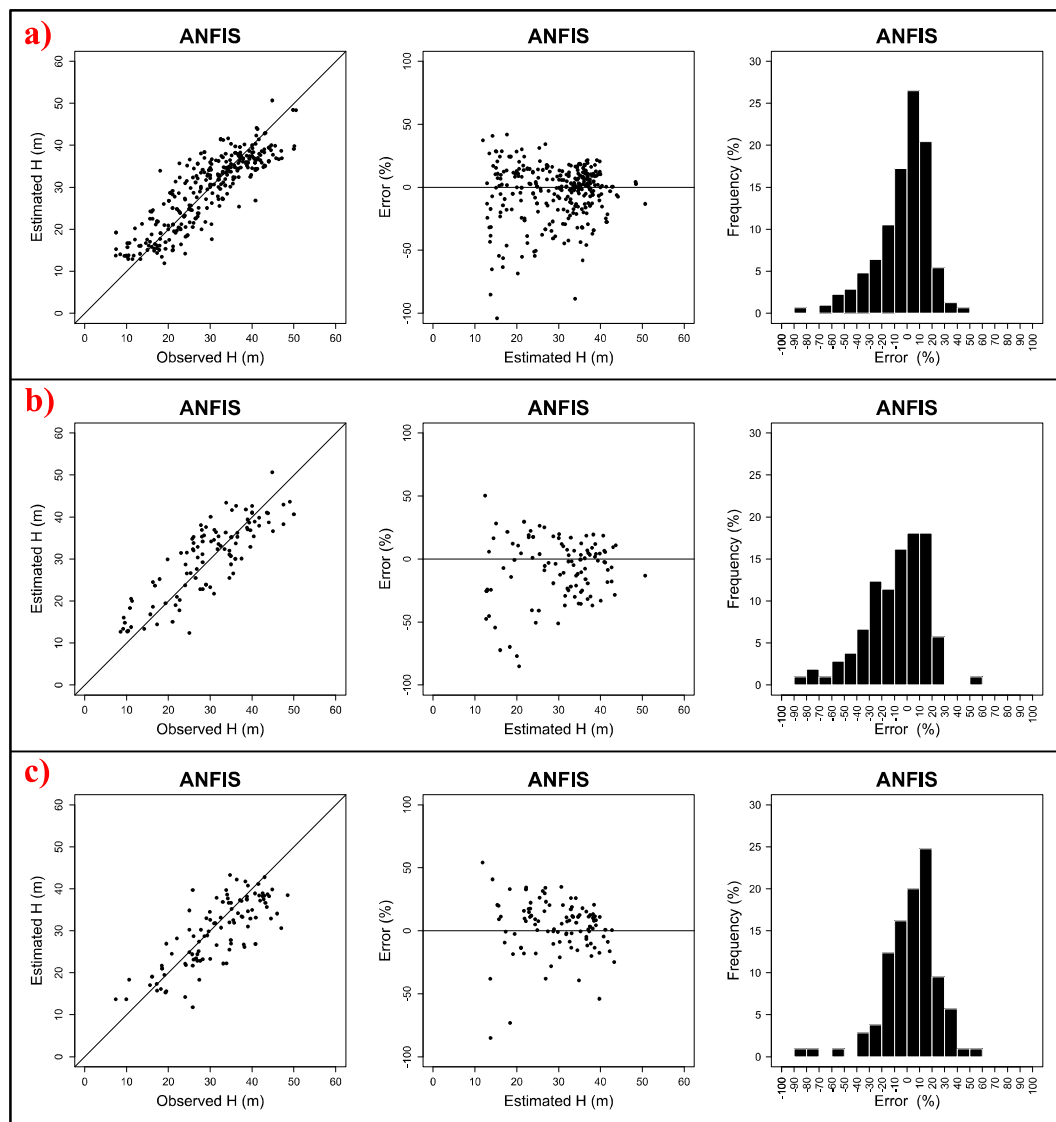


Figure 8. Estimated heights versus observed heights, distributions of percentage errors of height estimates, and histograms of errors of height estimates, obtained by ANFIS, for training (a), validation (b), and test (c) data.

4. Discussion

All modeling methods that predict forest performance, such as regression models and artificial intelligence models, have their own strengths and weaknesses. Although traditional regression models are capable of providing specific formulas, and these may make it easier to understand the relationships between variables in these models, these models have many limitations, including being independent of the range of statistical assumptions, such as a normal distribution of data, independence of variables, and so on [18,49,50]. One of the advantages of artificial intelligence techniques in stubborn modeling is that in many cases they do not have the same limitations of empirical models. For example, some assumptions (data normality and others) can affect the quality of empirical models. Other advantages of artificial intelligence techniques are the ability to work with qualitative variables and the relative accuracy and precision of these models [13], which are often well reported in predicting tree heights. According to our results (Table 7) artificial intelligence techniques had lower errors and more accurate estimations of tree heights in the study area, which is in line with the results of other studies [13,51–55].

The use of artificial intelligence techniques for forestry issues has become more and more popular recently, but is often limited to ANNs; other techniques such as ANFIS and fuzzy logic also have great potential for many forest modeling [13,56]. A *t*-test was performed to compare the results of R^2 and RMSE, and according to our results ($p \geq 0.005$), there was no significant difference between the accuracies of ANN and ANFIS models in estimating tree heights in the study area. This finding is consistent with the results of Vieira et al. [13], which concluded that artificial intelligence methods, including ANN and ANFIS models, can be of value for these purposes. In a study of the relationship between the diameters and heights of eucalyptus trees, Silva et al. [51] compared fuzzy logic and neuro-fuzzy models with classical mathematical models and concluded that neuro-fuzzy models had the highest accuracy and precision in predicting eucalyptus tree heights.

Our results complement prior research in this area. For example, Leite et al. [53] Diamantopoulou and Özçelik [55] used six nonlinear regression models as well as the GRNN (generalized regression neural network) method to estimate tree heights in the western Mediterranean Region Forests of Turkey. Consistent with the results of this study, validation statistics of their models showed that the GRNN model has both higher and lower error rates than other models. They attribute this to the ability to model nonlinear relationships to predict tree heights. Bayat et al. [18] used regression and ANN to predict the probability of tree survival in the Hyrcanian forests. They concluded based on model validation statistics, that ANN models were more accurate at predicting probability of survival and determining environmental affecting factors. These results are in line with the results of the present study. Zhou et al. [11] also reached a similar conclusion, and like the results of this study, they also concluded that the GRNN model had higher accuracy than the regression models in estimating DBH in the Zhejiang province in China. Lee et al. [57] used new three machine learning techniques, including support vector regression (SVR), modified regression trees (RT), and a random forest (RF) in South Korea to predict the heights of forest stands, and concluded that these three models were capable of estimating the height of stands well, and the estimates of these three models were not statistically significant. Finally, Bourque et al. [4] in Kheyroud forest used genetic programming to determine the relationship between height and diameter in beech forest and select the most environmental variables. In these studies, they proved the capability of AI approaches for prediction. Despite the differences in the types of neural network or artificial intelligence techniques used in all of these studies, or in the numbers of and types of model inputs, all of them are consistent with this research in illustrating the superiority of neural network and artificial intelligence methods over regression models.

To model the diameters and heights of *Beech* species in the northern forests of Iran, several different studies have been carried out, all of which used only nonlinear empirical models. Ahmadi et al. [22] used nineteen linear and eight nonlinear models for beech forest-type data and concluded these models could predict 70–76 percent of the variation in the dependent variable; among them Schnute, Weibull, and Richards models best predicted heights. Alijani et al. [58] used three diameter-height empirical models for beech species in unmanaged Kheyroud forests in northern Iran in three different successive stages. The results of this study indicate the suitability of relative function and Weibull models at early stages of forest development; the modified exponential at maturity; and Gompertz and Richards during the decay stage. Hamidi et al. [59] studied the diameter and height models of beech species in uneven-aged forest of northern Iran, and concluded that the Korf, Ratkowsky, Naslund, and Weibull models have good ability to accurately estimate beech tree heights. Therefore, nonlinear empirical models have often been used to investigate suitable models of beech height prediction in northern forests of Iran. However, the present study is unique in applying artificial intelligence methods to this purpose, which showed that ANN and ANFIS models are more capable of predicting the heights of beech species in northern Iran.

5. Conclusions

Forest management requires models that are accurate and capable of predicting important forest features, such as the diameters and heights of trees. According to our study and previous studies,

artificial intelligence models have the potential to complement and replace empirical models in forest modeling. The accuracy and ability to model complex relationships among variables are the main characteristics of a good and suitable model. For the cases modeled here, ANN and ANFIS models have a higher accuracy than empirical models in estimating total tree height, which confirms other studies on this subject: AI techniques can substitute for empirical models in efforts where forest conditions need to be estimated. In addition to ANN and ANFIS models being more accurate in our case study, they are more capable of modeling complex and nonlinear interfaces, and also have greater flexibility. Any one type of diameter-height model may not always be suitable for all types of conditions where a particular tree species might be found, because site conditions can affect the diameter–height relationship.

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