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Allometric Model Development for Above-Ground Biomass Estimation in Hyrcanian Forests of Iran

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Abstract: This research develops an allometric model for estimation of biomass based on the height and DBH of trees in theHyrcanian forests of Iran. An accurate allometric model reduces the uncertainty of allometric equation in biomass estimation using radar images. In this study, 317 trees were selected randomly from the 4 different dominant tree species for thedevelopment of an allometric model covering the wide range of DBH and height classes. The selected trees were measured with fieldwork in different parts and then volumes of these parts were calculated separately. Total volume of tree is obtained from the summation of these volumes.Twelve commonly used allometric models,threegeneralized modelsand a proposed model are tested and the most suitable model isselected based on some of the commonly measured statistical parameters coefficient of determination, Root-Mean-Square Error, Mean Error, Underestimated Error and Overestimated Error. We show that the biomass estimation accuracy is improved in a multilayer perceptron neural network when the density of wood and the tree measurements are used in combination compared to estimating the biomass by current allometric models. The RMSE value is decreased when the proposed method is used (RMSE =0.163mg and R^2=0.986) compared with Chave model as the best current method (RMSE =0.404mg and R^2=0.957) in this paper.

Key words: Allometric model · DBH · Height · Biomass · Hyrcanian forests

INTRODUCTION

Measurement of Above-Ground Biomass (AGB) is necessary for quantifying carbon biomass stores and for comparing result of remotely sensed methods in biomass estimation [1]. The method of biomass measurement can be divided into two groups i.e. direct and indirect [2]. The direct method involves the complete harvesting of sample plots and subsequent extrapolation to an area unit [3]. The indirect method aims to construct a functional relationship between tree biomass and other tree dimensions, such as stem diameter, height and wood density, by means of regression analysis [4]. Since the direct method is very time consuming, costly and completely destructive and biomass expansion factors (BEFs) are complex in nature, field observations of biomass are normally based on allometric models that approximate the biomass of the tree component or the total biomass of single trees according to easily measured variables, such as DBH or height.The term allometry means ‘the relationship between part of an organism and its whole [5].

Many studies have already developed allometric equations for different purposes, different regions and different species, for example species-specific allometric models [6-8], generalized allometric models [1-3, 9-12], allometric models for tropical forests [13-15], simplified allometric models [16, 17], allometric models for regional and global level biomass estimations [18-20] and there have even been studies on the uncertainty of using allometric models [21]. All of these models have been effective for specific purposes so far and there is no single optimal model which can provide a good calibration function for the estimation of AGB for all tree species and for all climatic regions because the calibration coefficients of allometric models are reported to vary with tree species, stand age, site quality, climate and the stocking of stands [22].

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Some studiesfound that the allometric equation could be generalized to make it useful for local to regional levels [4, 8,23], but they also recommended that an allometric model should be species-specific or site specific for its effective use, or calibration of coefficients be performed before its use inother places. There are two objectives of this paper. First, is development of an allometric model based on the dominant tree species in Hyrcanian forest of Iran for reduction of the uncertainties from generalized allometric equations and second is Improve the accuracy of estimated biomass using a multilayer perceptron neural network (MLPNN).

The paper is structured as follows. Section 2 provides the materials and methods, including a briefdescription of the study area, field data collection, relating volume to AGB, modeling and independent validation of AGB estimation models. Section 3 describes the results and discussion are presented.Finally, the study is concluded in Section 4.

MATERIALS AND METHODS

Study Area: The study area is located in Hyrcanian forests of Iranaround the Asalem forest (Fig. 1). The natural forest vegetation is temperate deciduous broadleaved forest that the main dominant trees of this forest are Fagus orientalis, Alnus serrulata, Carpinus betulus and Ulmus glabra.Figure 1 shows the coordinates of this area thatis considered as one of the rainiest areas in Iran which is a suitable habitat for the broadleafspecies. This research is conducted in three parcels with 171 hectares. Study areas are extended in range of 600-950 altitude from the sea level.

Data Collection: Hyrcanian forests of Iran are high forest and are managed using selection system method.Samples randomly were selected because the exact volume of the trees were should calculated. In some diameter classes specially the lower one, there are not sufficient cut trees in order to be used for sampling from the diameter classes. Hence completely random method is used instead of diagonal and height classes for sampling. Including the total cost of inventory, 317 samples were obtained. Trees are retrieved in the nature and desired characteristics were measured (Height and DBH) for this study.Minimum error and inventory costs are two determinant factors in samples components numbers [5]. Feld data collection was based on a stratified samplingmethodology. Trees were measured for each tree type inorder to achieve a desired precision level (in this case, an error levelof 10% expressed as the 95% confidence interval of the mean).

For determination of total volume calculation of trunk with over 20 cm diameters, firewood and stump volumesare necessary. Total volume of tree is obtained from the summation of these volumes. Volume of Trunks and branches were calculated using Smalian formula in 2 m pieces(Eq.1):

$$V_s = \pi l \left(d_L^2 + d_U^2 \right) / 8 \quad (1)$$

Where: V_s istrunk volume (m^3), l is piece length (m) and d_L and d_U are diagonals of trunk (m^3)at the beginning and the end of 2m piece, respectively.

Firewood volume of brancheswas divided into 1m pieces and their diameter was measured in the middle, then the volume of each branch was calculated by Huber formula (Eq.2):

$$V_f = \pi l \left(d_M^2 \right) / 4 \quad (2)$$

Where: V_f is firewood volume, l is piece length and d_M is diagonalof branch middle.

Stumpvolume was calculated from another form of Smalian formula (Eq.3) as follows:

$$V_t = \pi l \left(d_L^2 \right) / 4 \quad (3)$$

Where: V_t is Stump volume, H is piece length and $d_L$isdiagonal of treein cut location.

Finally total volume is the sum of trunk, firewood and stump volumes [5].

Relating Volume to AGB: In this paper forest volume data for calculation of biomass is used. Required data for this method is the volume for sample trees that was determined in section 2.3.AGB in megagram (mg) per hectare (ha)is estimated by Eq.4.

$$AGB = V \times WD \quad (4)$$

Where: AGB is above-ground biomass, V isvolume and WD isbasic density of the wood.

If we couldn't calculate volume, another way was estimation of volume by multiplying trunk volume (V_t) into BEFs [24].

Fig. 1: Positionof Asalem forest with broadleaf treesin North of Iran.

Table 1: Characteristics of field data. (Diameter at breast height(DBH) and Above-Ground Biomass(AGB)).

Row	Types	# of stands	Mean height (m)	Mean DBH(cm)	Mean Volume (m3)	Mean AGB (mg)
1	Fagus orientalis	92	27	58	4.034	2.936
2	Alnus serrulata	73	22	46	1.924	1.185
3	Carpinus betulus	80	21	45	1.853	1.601
4	Ulmus glabra	72	19	35	1.469	0.932

Wood density is defined as the mass of dry wood per green wood volume unit. Its unit is mg per m^3. In 1992, an equation (Eq.5) was developed to convert wood density with 12 percent moisture content into wood density based on dry mass per green volume[25].

$$WD = 0.0134 + 0.8 \times X \tag{5}$$

Where: *WD* is average density of the wood and *X* is wood density in 12 percent moisture.

Wood densitiesin 12 percent moisture for Fagus orientalis, Alnus serrulata, Carpinus betulus and Ulmus glabra species are 0.633, 0.535, 0.755 and 0.55, respectively [26]. Table 1 summarizes the ground measurements and resulting calculations.

Modeling: The relationship between the physical parameters (DBH or/and height) and the AGB of all harvested sample trees needed to be established in order to estimate the AGB of non-harvested trees. Although there are several empirical methods available, this study established this relationship using allometric equations because an allometric model is a useful tool which can approximate the AGB of single trees according to easily measured variables, such as diameter at breast height (DBH) or height (H) [13].

The most common allometric model in biomass studies takes the form of the power function [13] as follows:

$$AGB = a \times (DBH)^b \tag{6}$$

Where: *AGB* is the total above-ground biomass, *DBH* is the diameter at breast height,*a* and*b* are the scaling coefficient and scaling exponent, respectively. In most cases, the variability of *AGB* is largely explained by the variability of *DBH*. However, the values of *a*and *b* are reported to vary with species, stand age, site quality, climate and stocking of stands [22] and the most common problem with allometric equations is that the raw data are non-linear and tend to be heteroscedastic.

As such, the equation 6 cannot satisfy the relationship between AGB and the DBH. Hence, the standard method for obtaining estimates for the coefficients *a* and *b*is by the least-squares regression for *DBH* and *H* measured from destructively sampled trees and the form of the model will be as follows (7):

$$\ln(AGB) = \ln(a) + b \times \ln(DBH) \tag{7}$$

This transformation is appropriate when the standard deviation of *AGB*atany*DBH* increases in proportion to the value of *DBH* in many cases, log-transformation of real data results in homoscedasticity of the dependent variable *AGB*, a prerequisite for regression methods. However, even though the linear relationship of equation 7 mathematically equivalent to equation 6, they are not identical in a statistical sense and this transformation introduces a systematic bias that is generally corrected using a correction factor estimated from the standard error, but it has become conventional practice in allometric studies [27].

Different types of regression models and combinations of parameters have been usedincluding ordinary least squares on log-transformed data [2,8, 17], weighted least-squares regression on log-transformed variables [8] and non-Iinear regression [6, 15]. However, apparently there is no single optimal regression model that can give a good calibration function for the estimation of AGBbecause the values of coefficients are varied based on many factors [22]. Considering this situation, this paper tested different types of regression models for North of Iran including linear and non-linear, but most emphasis was placed on the methods of [1, 4, 13] as the work of these researchers used in recently remote sensing researches for estimation of biomass from SAR images [28-31]. Finally, proposed method was done with an MLPNN. A multilayer neural network is made up of sets of neurons assembled in a logical way and constituting several layers. Three distinct types of layers are present in the MLPNN. The input layer is not itself a processing layer but is simply a set of neurons acting as source nodes which supply input feature vector components to the second layer. Typically, the number of neurons in the input layer is equal to the dimensionality of the input feature vector. Then, there is one or more hidden layers, each of these layers comprising a given number of neurons called hidden neurons. Finally, the output layer provides the response of neural network to the pattern vector submitted in the input layer. The number of neurons in this layer corresponds to the number of classes that the neural network should differentiate [32].

The neural network that is used in this paper is arranged in layers as follows. The number of neurons in the output layer is taken to be equal to the estimated biomass. The input layer contains three neurons corresponding to the number of attributes in the input vectors. The input vector to the network for pixel *i* of the data sets is of the form $v_{ios} = \{v_{i1}, v_{i2}, v_{i3}\}$, where v_{i1} belongs to the height, v_{i2} belongs to DBH and v_{i3} belongs to wood density. After the determination of the input layer, the number of hidden layers required, as well as the number of neurons in these layers, still needs to be decided upon. An important result, established by the Russian mathematician Kolmogorov in the 1950s, states that any discriminate function can be derived by a three-layer feed forward neural network [32]. Increasing the number of hidden layers can then improve the accuracy of the fitting model, pick up some special requirements of the recognition procedure during the training, or enable a practical implementation of the network. However, a network with more than one hidden layer is more prone to be poorly trained than one with only one hidden layer.Thus, a three-layer neural network with the structure 3-2-1 (three input neurons, two hidden neurons and one output neurons) is used to fit a model to the data sets. Training the neural network involves tuning all the synaptic weights so that the network learns to recognize the given patterns or classes of samples sharing similar properties. The learning stage is critical for effective modeling and the success of an approach by neural networks depends mainly on this phase.

Independent Validation of AGB Estimation Models: Testing the goodness of fit of each model is very important in order to find the most suitable model for AGB estimation. The statistics of accuracy assessmentincluded the Root-Mean-Square Error (RMSE), mean error (ME) and the relative errors to the mean value of AGB. The value of the RMSE is affected by large errors which give disproportionately large weights because of the squaring process. The ME is a signed measure of error which indicates whether the predicted AGB isbiased. The predicted AGB is underestimated (UE) with a negative ME and overestimated (OE) with a positive ME. Additionally, thecoefficient of determination (R^2) was calculated as the square ofPearson's correlation coefficient.

RESULTS AND DISCUSSION

The Correlations between DBH and height with AGB were 0.93 and 0.86, respectively (Fig. 2). Thus using of these parameters together for modeling may had better result. The resultsof modelsare shown in Table 2. The simple regression models (Models 1, 2,and3) were not found to be good. The power-function models (Models 4, 5, 6) showed very good performances. The log-transformed models (models 7, 8 and 9)were found to be effective for AGB measurement because of the fact that log-transform has the potential to correct for the heterogeneous variance of AGB.The methods of [1, 4], [13] (Models 10, 12 and 14, respectively) using DBH, height and wood density achieved very good accuracies. Although we achieved better result thanthese models when we used sample data of North of Iran for calibration of coefficients of these equations (models 11, 13 and 15,

Table 2: Results obtained from different models for the development of an allometric model. (coefficient of determination (R^2), Root-Mean-Square Error (RMSE), Mean Error (ME), Underestimated Error (UE), Overestimated Error (OE) and Wood Density (WD)).

Row	Regression Model	Coefficient	Value of coefficient	R^2	RMSE (mg)	UE (mg)	OE (mg)	ME (mg)
1	AGB=a+b.DBH	a	-2746.03	0.873	0.696	-1.210	1.250	5.566
		b	96.54					
2	AGB=a+b.DBH.H	a	-1149.3	0.935	0.577	-0.983	1.052	5.133
		b	2.53					
3	AGB=a+b.DBH+c.H	a	-3894.65	0.896	0.631	-1.073	1.175	5.465
		b	73.64					
		c	95.89					
4	$AGB=(a+b.DBH)^2$	a	-7.89	0.909	0.590	-0.918	0.887	3.944
		b	0.99					
5	$AGB=a+b.DBH^c$	a	-367.30	0.911	0.579	-0.912	0.928	3.968
		b	0.87					
		c	2.01					
6	$AGB=a.DBH^b$	a	0.27	0.907	0.597	-0.871	0.865	4.083
		b	2.25					
7	ln(AGB)=a+b.ln(DBH)	a	5.86	0.869	0.809	-0.962	0.822	6.485
		b	0.03					
8	ln(AGB)=a+b.ln(H)	a	4.209	0.799	0.875	-1.835	1.107	7.592
		b	0.13					
9	ln(AGB)=a+b.ln(DBH)+c.ln(H)	a	-18904.5	0.906	0.761	-0.868	0.739	5.117
		b	3001.34					
		c	3011.46					
10	$AGB=a. (BDH^2.H)^b$	a	0.044	0.868	0.711	-0.939	1.386	5.681
		b	0.9719					
11	$AGB=a.(BDH^2.H)^b$	a	0.0611	0.946	0.453	-0.845	0.857	3.432
		b	0.9313					
12	$AGB=a+b.DBH+c.DBH^2$	a	21.297	0.827	0.812	-1.297	1.311	5.735
		b	- 6.95					
		c	0.740					
13	$AGB=a+b.DBH+c.DBH^2$	a	-228.437	0.909	0.588	-0.919	0.913	3.960
		b	-5.3679					
		c	0.91174					
14	$AGB=a. (WD.BDH^2.H)^b$	a	0.112	0.887	0.657	-0.845	0.757	4.181
		b	0.916					
15	$AGB=a. (WD.BDH^2.H)^b$	a	0.1173	0.957	0.404	-0.605	0.407	2.393
		b	0.928					
16	MLPNN	--	-----	0.986	0.163	-0.239	0.214	0.177

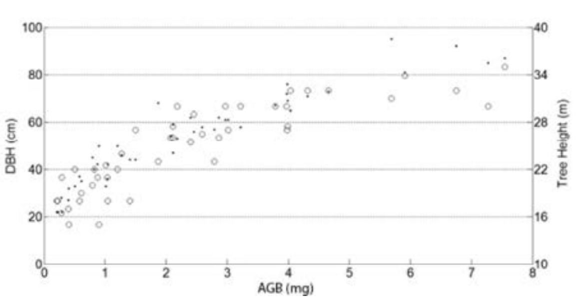

Fig. 2: Relationship between DBH (points), and height (circles)with AGB, respectively.

respectively).From the 15 models tested, model 15,orcalibrated model of[1]was found to give the best fit considering all of the statistic parameters among current methods. A fit of about 95.72%and a RMSE of 0.404mg were obtained using this model. This is very satisfactory in comparison with other allometric model but we developed a novel method based on neural network that had the best result among all current models.

The neural network is trained by using a back-propagation rule [33]. The numbers of training data are 222 samples (70% of all samples) with their wood density.

Theset of training patterns is presented repeatedly to the neural network until it has learned to recognize them. A training pattern is said to have been learned when the absolute difference between the output of each output neuron and its desired value is less than a given threshold. Indeed, it is pointless to train the network to reach the target outputs of zero or one since the sigmoid function never attains its minimum and maximum. The network is trained when all training patterns have been learned. Once the network is trained, the weights of the network are applied on the data sets to fitting model. The result of the neural network is shown in Table 2 in comparing with current models.For accuracy assessment and calibration, 95 samples (30% of samples) were selected as the test samples randomly. The values 98.6% and 0.163mg are achieved for R^2 and RMSE, respectively. It's the best result among current methods for biomass estimation.

In comparison between the MLPNN and current models, the advantages of MLPNN that is used in this paper are as follows:1) It can accept all kinds of numerical inputs, whether these conform to statistical distribution or not.2) It can recognize inputs that are similar to those which have been used to train them.3) Because the network consists of a number of layers of neurons, it is tolerant to noise present in the training patterns.

Table 2 shows that highest R^2 and lowest RMSE are related to models 1, 2 and 3 respectively among simple regression models. Better accuracy of model 2 (R^2=0.935, RMSE=0.577 mg) compared to model 1 is due to DBH and height parameters use for modeling whereas in model 1 (R^2=0. 873, RMSE=0. 696 mg) only DBH was applied. Probably the use of summation between DBH and height parameters leads to accuracy reduction in model 3(R^2=0. 896, RMSE=0. 631 mg) than model 2. As can be seen in figure 3 in model 2, the density is high around $y=x$ line where proximity of these points to this axis indicates low ME, OE and UE in this model compared to models 1 and 3. Values of this error for each model are shown in table 2 separately.

Model 12 in table 2 represents model of [13] which is a second-order polynomial according to DBH but in contrast to models 1,2 and 3 has lower R^2 (0.827) and higher RMSE (0.812 mg). It shows how the use of theunivariategeneralized model with no calibrated coefficients can cause error in AGB estimation. The model uncertainty greatly increases when this relation is applied as a source.Model 12 coefficients calibration based on the local data leads to model 13 which increases R^2 up to 0.909 and decreases RMSE to 0.588. Model 13 errors declined sharply compared to model 12 as table 2 shows. Figure 3 indicates that density of points around identity line ($y=x$ line) in model 12 is low which increases in model 13 after coefficients calibration. Results reveal that coefficients calibration of [13] can made accuracy of AGB estimation increased. However sufficient ground data of different species should be existed for calibration. In general the optimal model (model 13) is proposed for those forests that have not feasibility to measure trees height due to their age or high density. Thus, only by measuring trees DBH and applying model 13, desirable accuracy for AGB estimating can be obtained.

Among models based on the power function, highest R^2 and lowest RMSE are related to models 5, 4 and 6 respectively. Better accuracy of model 5 (R^2=0.911, RMSE=0.579 mg) compared to model 4 (R^2=0.909, RMSE=0.590 mg) is due to the lack of power factor for offset. While accuracy is reduced in model 6 by eliminating offset. The ME, OE and UE of each model is represented in table 2. In general, with respect to the use of DBH in power functions singly, acceptable accuracy was obtained for these relationships.

Model 10 in table 2 is [24] which is apower function model based on DBH and height. As table 2 shows although this model uses both DBH and height parameter but has the lowest R^2 and highest RMSE (R^2=0.868, RMSE=0.711 mg) compared to the other power-function such as 4, 5 and 6 models which are all univariates. In addition to R^2 and RMSE, the comparison of errors indicates that applying theunivariate model with integer coefficients may leads to better consequence in contrast to a multivariate generalized model with non-calibrated coefficients. With calibrating the coefficients of model 10 according to local data, model 11 is obtained which makes R^2 increased (0.946) and RMSE (0.453 mg) decreased. Table 2 shows errors reduction in model 11 compared to model 10. As figure 3 represents density of points around identity line is low in model 10. After calibration of coefficients and producing model 11 the density of points is highly increased. Results indicate that with the coefficients calibration of [24] the accuracy of AGB estimation can be greatly increased into desirable extent. Generally optimized model of brown *et al*, 1992(model13) is proposed for those forests which have measurement feasibility of trees height with DBH. Therefore measurement of trees height, DBH and coefficients calibration suited to local species leads to highest accuracy for ground biomass estimation by [24].

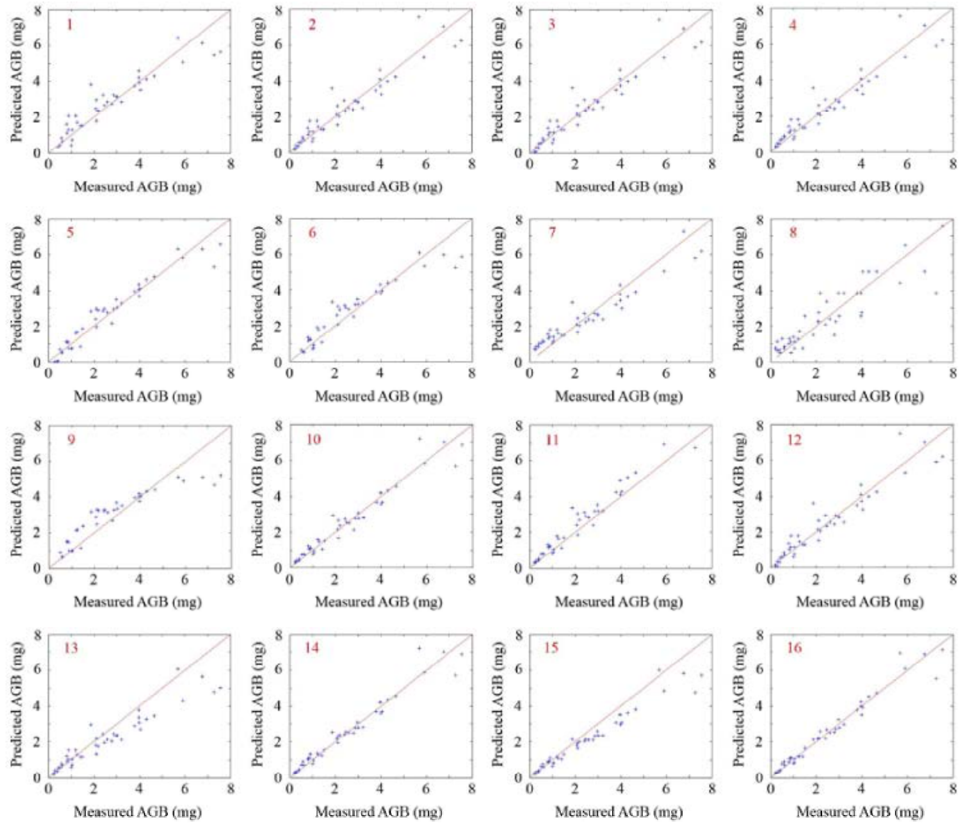

Fig. 3: Performance of different allometric modelsagainst MLPNN model.

Among models based on logarithmic transformation, highest R^2 and lowest RMSE are belong to models 9,7 and 8 respectively. Better accuracy of model 9(R^2=0.906, RMSE=0.761 mg) compared to two other models is due to the use of both DBH and height parameter for modeling, whereas in model 7(R^2=0.869, RMSE=0.809 mg) only DBH and in model 8(R^2=0.799, RMSE=0.875) only height was used for modeling. Nonetheless DBH-based models are more accurate than height-based models. In the case of ME, OE and UE, this sequence can also be expressed for logarithmic models. Although model 9 has the best performance among logarithmic models but is not superior to other methods and compared with the model 11, the model cannot be considered accurate. As figure 3 illustrates, the density of points along identity line in model 9 is better than 7 and 8 models.

Model 14 demonstrated in table 2 is [1] model which is apower function model based on the wood density, DBH and height that has been applied in most recent remote sensing papers. The basic pattern is [24] with the difference that the density of trees species has been considered in allometric relation in order to estimate AGB. This model has R^2=0.887 and RMSE=0.657 mg compared to the other two models (10, 12), higher accuracy is obtained. But calibration of [1] using local data and improved optimized model for the north of Iran, the best performance among all allometric models in biomass estimation was observed. As can be seen in table 2, model 15 with R^2=0.957 and RMSE=0.404 mg has a better result compared to other methods that have been investigated yet. Model 15 is distinct from 1 up to 14 models as shown in figure 3. Using optimized model that is proposed for those forests that besides DBH and height measurement feasibility have available data related to the density of trees species. Applying this model the uncertainty of allometric equation in biomass estimation by radar images can be greatly reduced because the main reference of ground forest biomass estimation for remote sensing investigations is allometric relations. Finally the considered model of this study was implemented using the MLPNN. Model 16 in table 2 is developed based on neural networks. This model leads to more accurate result than current methods and highest R^2(0.986) and lowest RMSE (0.163 mg) are obtained among all models. Also there is significant difference in ME, OE and UE compared to the rest of methods. Figure 3 shows that model 16 has more brilliant performance among all models. High density of points around identity line and along the axis represents the accuracy of this model. In general, after MLPNN model,power function, logarithmic and simple regression models have the best accuracy respectively for biomass estimation.

CONCLUSION

Hyrcanian forests of Iranis thetemperate deciduousbroadleaved forest that mustbe met through scientificresearch aimed at reducing carbon emissions through abetter land use/land cover management. Therefore, an accurate andspatially explicit AGB of the forest cover of Hyrcanian forests isparamount if carbon stocks and respective changes over time are tobe quantified and assessed. It is often difficult to transfer a developed model of a specific study area to another due to many factors, such as tree species, stand age, site quality, climate and the stocking of stands which could affect the success of model transferability. This study aimed at modeling a novel allometric model from field data. Many different modeling approaches were tested and a proposed model was selected for biomass estimation. We have shown that the biomass estimation accuracy was improved when MLPNN was used in comparison to estimating the biomass by using the generalized allometric models and no need calibration.The proposed methods wereassessed and resulting a RMSE of 0.163 mg and coefficient of determination between observed and predicted AGB values of 0.986.However, accuracy of model with using the wide range of tree species for a regional context would be better in future research.

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