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Research Article

Improving the Efficiency of Allometric Equations Using Artificial Neural Networks in Coppicing Stands of Brant's Oak

Saman Fallah, Javad Soosani*, Hamed Naghavi, Mohsen Yousofvand Mofrad

Forestry Agriculture and Natural Resources Faculty, Lorestan University, Khorramabad, Iran

Abstract

Estimation of forest trees biomass for various purposes is fundamental and substantia l. One method of estimating biomass uses allometric equations that limit the normality of variables and the homogeneity of variances. In this study, artificial neural networks were used as an alternative method to increase biomass estimation accuracy. Fifty three sprout chumps of Brant's Oak (*Quercus brantii* Lindl) were randomly selected from the Melah Shabanan of Khorramabad in Iran. Diameter at knee height, diameter at breast height, crown diameter, number of sprouts, and height of trees were measured. To calculate the dry weight of the biomass, adisk3-5cm from the trunk and crown was separated and weighed, and with the ratio of dry weight to fresh weight, the dry weight of the crown, trunk, and aboveground biomass of the trees was calculated. Modeling the relationships between variables with linear and nonlinear regression equations and Multilayer Perceptron and Radial Basis Function neural networks showed that both neural networks could increase the coefficient of determination to R^2=0.98 and R^2=0.96 and reduce the error to RMSE%=11.6 and RMSE%=16.9 and thus the neural network models can increase the quality forest biomass estimates are compared with allometric equations.

Keywords

MLP and RBF Network, Linear and Nonlinear Regression Equations, Aboveground Biomass

1. Introduction

In addition to providing various goods and services to humans, forests have a vital role in natural carbon storage on a global scale. Therefore their protection is one of the most important and sustainable strategies deal with global warming [20]. Biomass Estimation is also essential in evaluating forests' structure and state [23], estimating carbon production and flow, and assessing the fertility of an area [28].

The Zagros forests cover a large area of western Iran, up to 6 million hectares. These veteran forests perform important functions in the regions geography, such as a continuous fresh water supply, soil protection, climate change control, and maintainings socio-economic balance in western Iran [38].

The allometric equations are among the best in direct methods for estimating biomass and carbon in forest trees. Allometry describes changes in one character based on another [26]. Since the direct measurement of total tree biomass is very time consuming and involves high costs, establishing the allometric equations while considering the variables such

*Corresponding author: Soosani.j@Lu.ac.ir (Javad Soosani)

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as diameter at the breast height, height, bole, branch or crown diameter has attracted several researchers and experts [1, 12, 27, 14, 37].

However, there are limitations in using allometric equations as the data must be regular with the homogeneous variances. Moreover, no alignment or autocorrelation exists between the independent variables [40]. The artificial neural networks (ANNs) are among the methods providing a lower error than allometric estimates. ANNs are indeed one of the most important subsets of modeling and simulation of artificial intelligence systems [30].

The ANNs, a method resembling the human brain and neural neurons, are widely used in many sciences. A set of these neurons connected by narrow strands is responsible for learning in humans. Hence, they are known as ANNs in biological sciences and artificial intelligence.

In other words, the neural network can be considered as an electronic model of the human brain structure [39].

The ANN structure comprises several processing elements (PE) or interconnected nodes. These elements are organized in neuron layers (three input, output, and hidden layers). PE in these layers are wholly or partially related [35].

The neural network has many advantages over traditional statistical methods such as regression. One of the essential advantages of this network is that there is no need to hypothesize about the relationship between independent and dependent variables in modeling. Instead, relationships are determined during the learning process [29]. Other advantages of ANN over classical statistical methods are high processing speed, complex simulations, no dependence on statistical data distribution, and adaptability to changing environmental conditions [5].

In general, neural networks can be used to solve problems such as pattern classification, clustering, function estimation, forecasting, optimization, content-based retrieval, and process control [15].

Coulson (1987) used ANNs for the first time as an alternative method for modeling complex and nonlinear forest science phenomena [7].

The most important fields of work of the artificial neural network in forest sciences are mapping and classifying forest lands, modeling forest growth and dynamics, analysis and modeling of spatial data, and research related to climate change [35]. So far, the ANN has been used in different parts of forestry, for example, for predicting tree volume [33], total tree height [32, 3], bark volume [9], estimation of biomass [31, 42], individual tree-based basal area and volume increment models [2, 4], and diameter distribution of trees [9, 21, 10].

As mentioned, estimating tree biomass is one of the most important artificial neural network applications. Studying the complex and unknown relationship between dendrometric dimensions of trees and biomass in natural forest ecosystems with artificial neural networks is better than regression equations [42].

The most widely used neural networks in natural resource sciences are MLP or multilayer perceptron and RBF or radial base function. There are at least three-node layers (i.e., one input, output, and one hidden) in an MLP network. Except for the input nodes, each node is a neuron using a nonlinear activation function. A perceptron receiving vectors of inputs with actual values calculates a linear combination of these inputs. TanhAxon, SigmoidAxon, Linear TanAxon are among the activation functions in this network. Classification methods primarily used in RBF networks work within a shorter time compared to the MLP method. The types of layers in this method are the same as MLP, except that only one hidden layer exists in RBF. Gaussian functions are this method's most important activation functions [29].

Several parameters such as number of neuron layers, number of neurons per layer, transmission functions, learning law, learning factor ratio, number of learning cycles are required to determine the best neural network architecture or topology. Error is measured between training and test processes using root mean square error (RMSE) [6]. Known data is trained and then tested with data that does not participate in the training process.

Brant's Oak (*Quercus brantii* Lindl) is a oak species native to Iran, northern Iraq, eastern Turkey, and Syria. This species covers more than 50% of the Zagros Mountains [22]. However, the area of these forests has been affected in recent decades due to land degradation for crop cultivation, over-exploitation of non-timber crops, and overgrazing. Sustainable management of Zagros forests needs information to understand and predict changes in the conditions of these forests. Aspects that need to be assessed are the forest structure and its restoration, closely related to the exploitation of forests and their products. Forest aboveground biomass or AGB is a variable that broadly indicates the structure and function of the forest. The diversity of Brant's Oak sites in a wide area of the Zagros and different latitudes requires extensive study to achieve allometric relationships in each site. These relationships are useful in determining the volume per hectare and other quantitative components of the stand, measuring the amount of carbon deposited, and extracting the map of carbon sequestration. So far, several studies have been performed on the efficiency of allometric equations in estimating the biomass of different species of Iranian oak, including Iranmanesh et al. (2013) and Mahdavi et al. (2020). [18] and [24].

According to the explanations provided in this research, the following goals are pursued:

1. Determining the appropriate equations for estimating the aboveground biomass (AGB) of Brant's Oak species using linear and nonlinear regression methods in the MeleShabanan region of Khorramabad
2. Determining the best independent variable (from diameter at knee height, diameter at breast height, crown

diameter, total height, and number of sprouts) to estimate the best and most appropriate allometric relationship in AGB calculation
3. Comparison of MLP and RBF neural network capabilities with allometric equations in AGB estimation

Traditionally, the first two goals can be achieved using allometric equations, but the goal here is to reduce error and increase the accuracy of estimates.

2. Materials and Methods

Lorestan province is located in western Iran. This province is one of the rich forest resources of the Middle Zagros in Iran and has four climates: semi-arid, mild semi-humid, semi-humid, cold and highland climate.. city of Khorramabad, as the central of Lorestan province, has a mild semi-humid climate. The study area is located in parts of Shurab or MeleShabanan forests of Lorestan province in 15 km of Khorramabad-Dore Chegni road between 33° 30′ 57″ to 33° 31′ 22″N and 48° 11′ 5″ to 33° 29′ 4″E with the altitude of 1200 to 1400 m above sea level (m.a.s.l).

The main species of this site is *Quercusbranti*. This area includes limestone and an average rainfall of 411.2 mm. The average temperatures of the coldest (January) and warmest (August) months are 5.5 and 30.6℃, respectively.

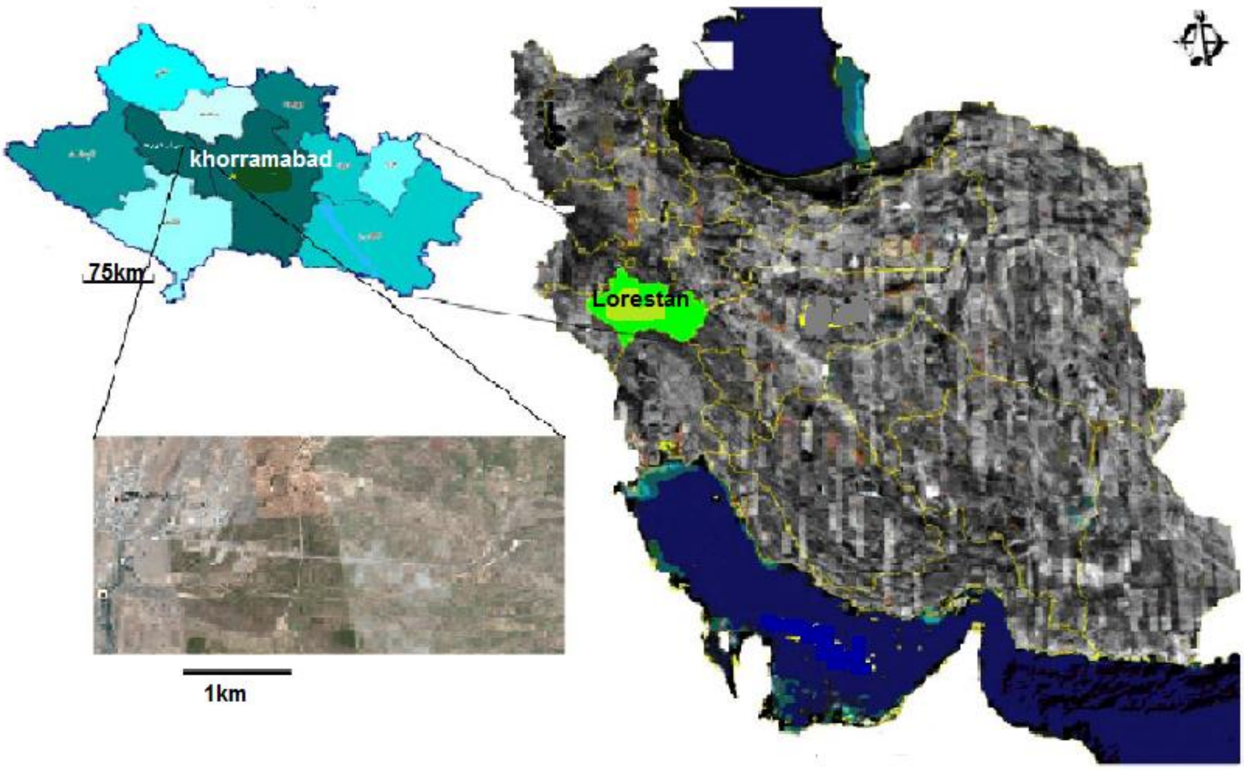


Figure 1. *Study are allocated inLorestan province (Khorramabad).*

A preliminary site visit was performed in the study area, and the areas with homogeneous topographic and physiographic status were selected. Then, the proper areas for taking samples were determined, and 53 sprout chumps of Brant's oak species were randomly based on the nearest neighbor to the random point by GPS selected and marked. Afterward, the following variables were measured in the selected trees: crown diameter (cd), diameter at breast height (d), diameter at the knee height (dk) (at the height of 50 cm above the ground), and the height (h) and number of sprouts of each tree (ns). Each cut tree was sliced into smaller pieces after cutting down the marked trees in the winter. The wet weight of the trunk and crown were separately determined in the field. Next, different parts of the tree were weighed using a digital scale with an accuracy of 0.1 kg. A disc with a thickness of 3-5 cm was cut from the tree's trunk. Moreover, from the crown of each tree, a piece of branch with a length of 10 cm was randomly cut and weighed. In the next step, the dry weight of the samples was determined after oven drying them at 105℃ for 48 h. Finally, the moisture ratio was determined for each tree using the weight of dry and wet samples. The dry weight of different parts of the trees was calculated as follows:

$$\mathrm{DW}_t = \frac{DW_S}{FW_S} \times FW_t \tag{1}$$

Where DW_t is the total dry weight, FWs is the sample's fresh weight, and DW_s is the sample dry weight. Modeling was performed using linear multiple regression analysis through two stepwise and entire methods. To this end, non-linear regression methods including logarithmic, inverse, quadratic, cubic, combined, power, growth, and exponential equations were also used. SPSS ver.17 was used for the calculations.

$$Y=b_0+b_1x \tag{2}$$

(linear)

$$Y=b_0+b_1LnX \tag{3}$$

(logarithmic)

$$Y=b_0+b_1/X \tag{4}$$

(reverse)

$$Y=b_0+b_1x+b_2x^2 \tag{5}$$

(quadratic)

$$Y=b_0+b_1X+b_2x^2+b_3x^3 \tag{6}$$

(cubic)

$$Y=b_0+b_1^X \tag{7}$$

(combined)

$$Y=b_0X^{b1} \tag{8}$$

(power)

$$Y=e^{b_0+b_1X} \tag{9}$$

(growth)

$$Y=b_0e^{b_1X} \tag{10}$$

(exponential)

NeuroSolution 5 was used to analyze the built ANNs. The most common ANN architectures in this program are MLP, PCA, RBF, SOM, and SVM.

MLP and RBF methods were used in network design. In artificial network design, all data were first standardized using Eq. (11) and scaled between 0 and 1 to increase the accuracy and speed of network training.

$$z = \frac{(X_i - X_{min})}{X_{max} - X_{min}} \tag{11}$$

Where Z is the standardized data, X_i is the data used, and X_{max} and X_{min} are the maximum and minimum data in each variable.

The TanhAxon activation function from the linear axon class was used in both methods. Each neuron in each layer in the TanhAxon function is assigned with hyperbolic tangent function within the range of -1 and +1 as follows:

$$f(x_i, w_i) = tanh\begin{bmatrix} lin \\ x_i \end{bmatrix} \tag{12}$$

The performance of different models was assessed using cofficieant of ditermination (R^2), root mean square error percent (RMSE%), mean absoulot error (MAE%), coefficient of variation (CV), and bias percentage (Bias%). These statistics are calculated between the observed and the predicted values to determine the superiority of the models. These statistics can be obtained using the following equations:

$$R^2 = 1 - \sum \frac{(\hat{y}_i - y_i)^2}{\sum \hat{y}_i{}^2} \tag{13}$$

$$RMSE\% = \frac{RMSE}{\bar{y}} \times 100 \tag{14}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{15}$$

$$CV(RMSE) = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{16}$$

$$MAE = \sum_{i=1}^{n} \left| \frac{(\hat{y}_i - y_i)}{n} \right| \tag{17}$$

$$MAE\% = \frac{MAE}{\bar{y}} \times 100 \tag{18}$$

$$Bias = \sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)}{n} \tag{19}$$

$$Bias\% = \frac{Bias}{\bar{y}} \times 100 \tag{20}$$

where y_i is the measured biomass, $\hat{y}$ is the predicted biomass, $\bar{y}$ is the mean measured biomass and n is the number of measured samples.

3. Results

First, the normality hypothesis of the prepared data was checked and confirmed using the Kolmogorov-Smirnov test. Examining the out-of-date data revealed no outlier data.

Allometric regression equations were modeled using the crown diameter (cd), diameter at breast height (d), diameter at knee height (dk), tree height (h), and the number of sprouts (ns) as an independent variable (estimator) and total tree weight as a dependent variable or y (estimated). Table 1 presents the descriptive statistics for each variable.

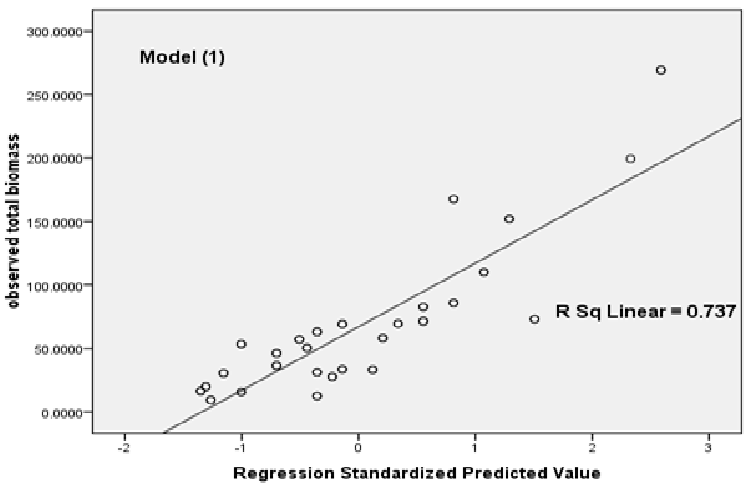
Table 1. Descriptive statistics of Brants Oak trees used to develop models.

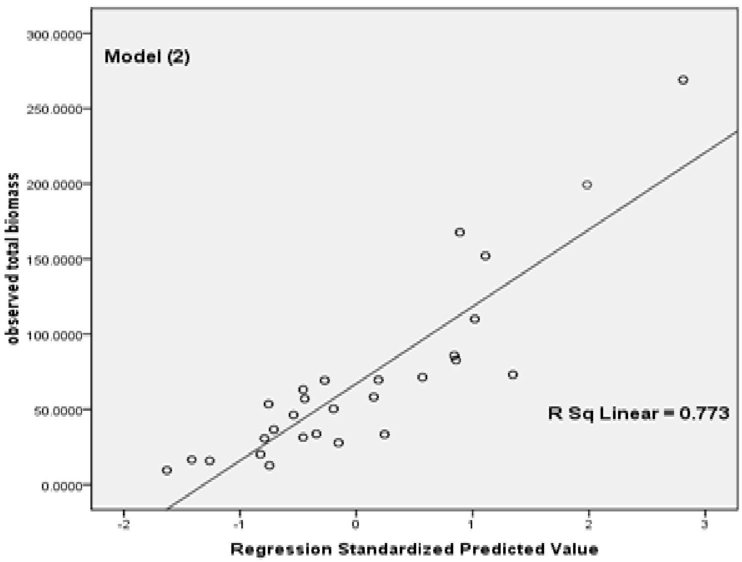
NumberofSprout			DiameteratKneeheight (cm)			Height (m)			Diameteratbreastheight (cm)			CrownDiameter (m)		
Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min
16	4.47	1	19.7	1.24	5.09	5.8	3.89	2.60	19.1	1.154	4.46	6.50	3.51	1.95

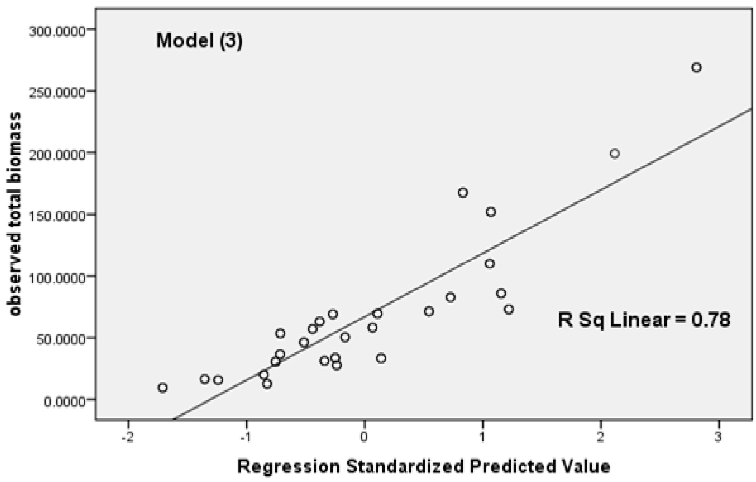
According to the results of multiple linear regression fitting using the entire method for estimation of the tree biomass, the highest coefficient of determination (R^2 = 0.823) is obtained using the multiple linear models with variables of crown diameter, diameter at breast height, height, and diameter at knee height, and the number of sprouts (Model 5 in Table 2). The RMSE in model 5 (40.08) and the bias percentage in model 1 (0.005) are less than other models. The results also revealed that increasing the number of variables increases R^2 while reducing the error indices of RMSE% and MAE%.

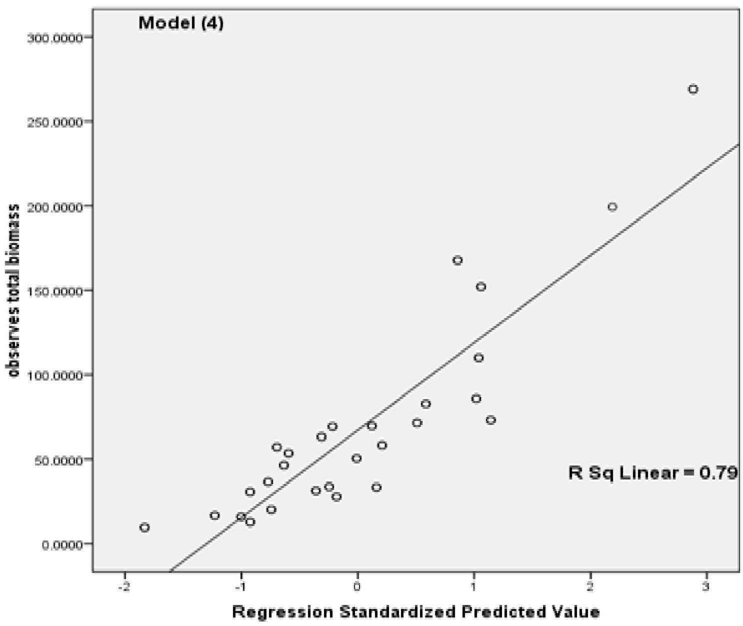
Table 2. The result of evaluating the multivariate regression method in estimating treebiomass according to the type and number of variables (by entire method)(X1=Crown Diameter, X2=Diameter at breast height, X3=Tree Height, X4=Diameter at Knee Height, X5=Number of Sprout).

Form	Model	F	Std.estimate	Bias%	RMSE %	CV(RMSE)	MAE%	R^2
1	Y=-84.76+43.279X1	148.82	30.11	0.005	45.1	0.44	31.39	0.74
2	Y=-112.299+38.364X1+3.889X2	88.73	28.02	0.01	42.2	0.41	29.3	0.77
3	Y=-134.878+35.367X1+3.267X2+10.400X3	60.266	29.12	0.18	41.8	0.41	27.06	0.78
4	Y=-149.020+34.318X1+1.522X2+12.011X3+2.569X4	47.43	27.7	0.33	41.41	0.41	19.8	0.797
5	Y=-156.713+26.091X1+2.818X2+10.694X3+3.399X4+4.214X5	40.78	28.39	0.28	40.1	0.4	27.01	0.8




Model (2)
observed total biomass
300.0000
250.0000
200.0000
150.0000
100.0000
50.0000
0.0000
R Sq Linear = 0.773
-2
-1
0
1
2
3
Regression Standardized Predicted Value


Model (3)
observed total biomass
300.0000
250.0000
200.0000
150.0000
100.0000
50.0000
0.0000
R Sq Linear = 0.78
-2
-1
0
1
2
3
Regression Standardized Predicted Value


Model (4)
observes total biomass
300.0000
250.0000
200.0000
150.0000
100.0000
50.0000
0.0000
R Sq Linear = 0.79
-2
-1
0
1
2
3
Regression Standardized Predicted Value

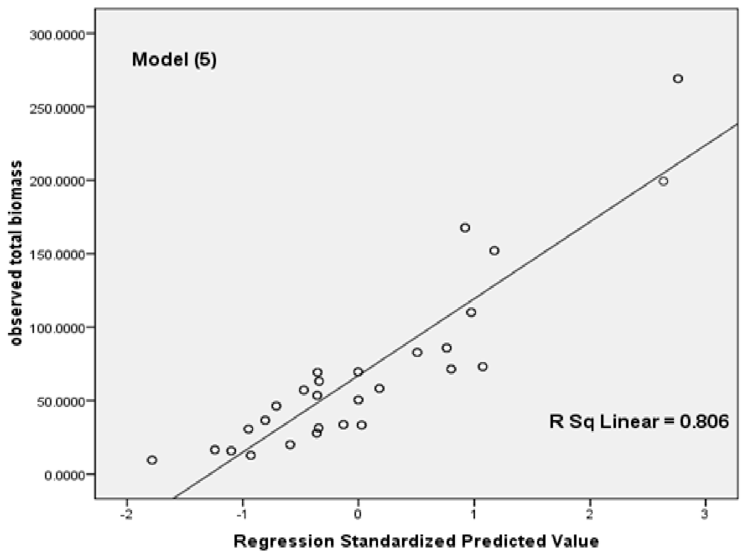


Figure 2. Comparison of actual biomass output with biomass output predicted byentire regression analysis method (models 1 to 5).

Results of Estimating the Biomass with Nonlinear Regression Equations

In this section, the tree biomass was calculated based on the independent variables of crown diameter, diameter at breast height, height, diameter at knee height, and the number of sprouts. For this purpose, we used linear, logarithmic, inverse, quadratic, cubic, combined, power, growth, and exponential equations.

Table 3. Results of regression for selecting the model estimating biomass trees (kg) in Brant's oak of Melah-Shabnan Khorramabad (p<0.05).

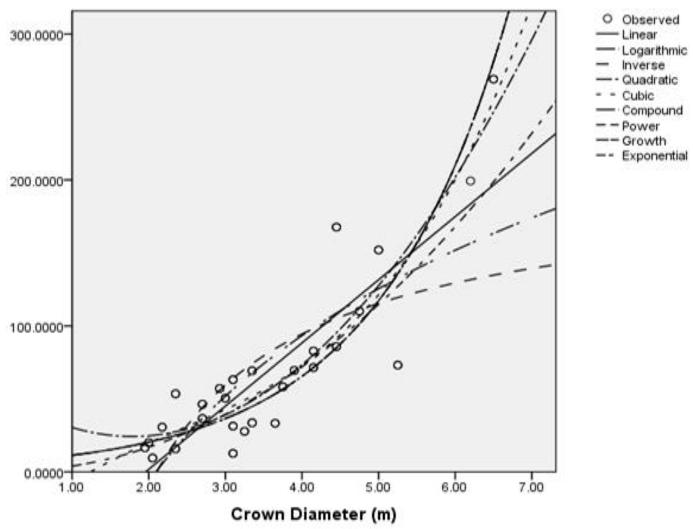
Model	CV(RMSE)	RMSE %	R^2	Std.errorofestimate	F	Model-type	Estimatorvaria-ble
Y=-84.76+43.28X	0.44	45.1.8	0.74	30.11	148.82	Linear	
Y=-106.610+144.239Lnx	0.52	53	0.63	35.524	91.972	Logarith-mic	
Y=199.336-419.497/x	0.6	61.01	0.52	40.833	56.723	Inverse	
$Y=56.25-35.605X+9.985X^2$	0.38	38	0.82	25.375	116.068	Quadratic	
$Y=-51.267+55.560X-13.887X^2+1.932X^3$	0.38	38	0.82	25.306	78.213	Cubic	Crowndiameter
$Y=6.366+1.791^X$	0.007	0.65	0.7	0.445	123.27	Compound	
$Y=3.965X^{2.091}$	0.007	0.65	0.69	0.447	122.178	Power	
$Y=e^{1.851+0.583X}$	0.007	0.65	0.69	0.445	123.27	Growth	
$Y=6.366e^{0.583X}$	0.007	0.65	0.714	0.445	123.27	Exponen-tial	
Y=-50.432+10.181X	0.74	73.6	0.32	48.63	24.37	Linear	
Y=-160.421+94.757lnx	0.75	75.2	0.27	50.311	19.277	Logarith-mic	
Y=137.058-730.640/X	0.8	79	0.2	52.142	14.289	Inverse	Diameteratbreast
$Y=48.566-8.669.X+0.827X^2$	0.71	71	0.36	47.421	14.677	Quadratic	
$Y=-352.865+114.980X-10.577X^2+0.32$	0.64	64.7	0.48	43.268	15.574	Cubic	

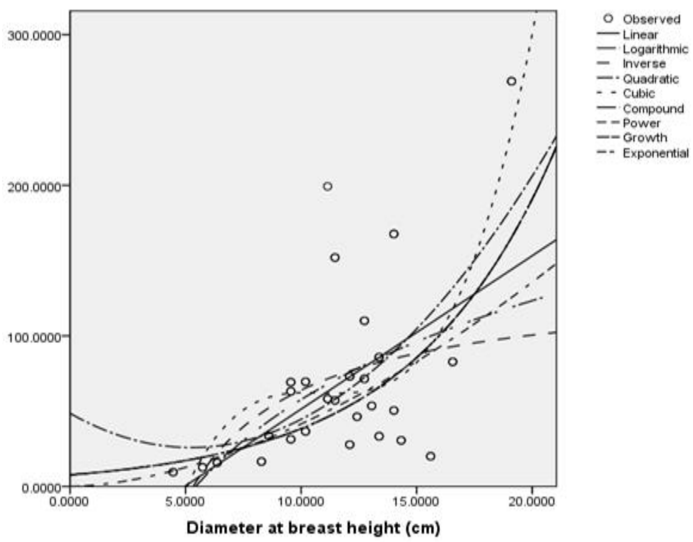
Model	CV(RMSE)	RMSE %	R^2	Std.errorofestimate	F	Model-type	Estimatorvariable
$3X^3$							
$Y=7.729+1.174^X$	0.009	0.95	0.38	0.625	36.604	Compound	
$Y=0.814X^{1.708}$	0.008	0.91	0.441	0.601	43.975	Power	
$Y=e^{2.045+0.159X}$	0.009	0.93	0.4	0.625	36.604	Growth	
$Y=7.729e^{0.160X}$	0.009	0.93	0.4	0.625	36.604	Exponential	
$Y=-167.527+60.804X$	0.65	65.34	0.45	43.728	42.676	Linear	
$Y=-263.722+247.273LnX$	0.65	65.32	0.44	43.714	42.735	Logarithmic	
$Y=312.981-925.972/X$	0.66	65.9	0.42	44.65	38.74	Inverse	
$Y=-305.305+127.859X-7.912X^2$	0.65	65.5	0.45	43.81	21.66	Quadratic	
$Y=-288.988+105.202X-0.799X^3$	0.65	65.17	0.46	43.611	22.095	Cubic	Height
$Y=1.533+2.457^X$	0.008	0.84	0.51	0.569	55.155	Compound	
$Y=0.290X^{3.838}$	0.008	0.84	0.55	0.537	55.155	Power	
$Y=e^{0.427+0.905X}$	0.008	0.85	0.51	0.589	55.155	Growth	
$Y=1.533e^{0.905X}$	0.008	0.83	0.517	0.569	55.155	Exponential	
$Y=-46.259+9.175X$	0.7	76	0.25	50.867	17.71	Linear	
$Y=-158.781+91.214LnX$	0.7	78.2	0.208	52.316	13.842	Logarithmic	
$Y=134.622-767.928/X$	0.81	80.3	0.162	53.778	10.258	Inverse	
$Y=76.843-12.550X+0.894X^2$	0.74	74	0.303	49.51	11.318	Quadratic	
$Y=-377.057+107.611X-10.430X^2+0.305X^3$	0.7	69	0.405	46.195	11.576	Cubic	DiameteratKnee
$Y=10.674+1.132^X$	0.001	1.05	0.24	0.709	16.556	Compound	
$Y=1.472X^{1.417}$	0.001	1.04	0.26	0.698	18.757	Power	
$Y=e^{2.368+0.124X}$	0.001	1.05	0.24	0.709	16.556	Growth	
$Y=10.674e^{1.24X}$	0.001	1.05	0.24	0.709	16.556	Exponential	
$Y=17.488+11.109X$	0.7	74.2	0.284	49.698	21.071	Linear	
$Y=10.208+43.888LnX$	0.7	75.7	0.256	50.665	18.269	Logarithmic	
$Y=99.455-93.453/X$	0.79	79.5	0.18	53.176	11.699	Inverse	
$Y=15.059-12.163X-0.830X^2$	0.75	74.9	0.289	50.156	10.359	Quadratic	NumberofSprout
$Y=-1.366+24.021X-2.091^2+0.086X^3$	0.7	75.3	0.29	50.435	6.974	Cubic	
$Y=26.286+1.151^X$	0.001	1.05	0.24	0.709	16.517	Compound	
$Y=22.994X^{0.587}$	0.001	1.04	0.24	0.708	16.708	Power	

Model	CV(RMSE)	RMSE %	R^2	Std.errorofestimate	F	Model-type	Estimatorvariable
$Y=e^{3.269+0.147X}$	0.001	1.05	0.24	0.709	16.517	Growth	
$Y=26.288e^{0.14X}$	0.001	1.05	0.24	0.709	16.517	Exponential	

As shown in Table 3, in most variables (except height) in the quadratic and cubic linear equations, R^2 considerably increases compared to the logarithmic equations and types of power equations. Another critical point is the increase in the R^2 in the crown variable (up to 0.835) in the quadratic equations and its significant decrease in other independent variables (i.e., diameter at the breast height, height, diameter at the knee height, and the number of sprouts, in the order of their appearance). However, regarding the obtained RMSE% and CV (RMSE), it is observed that the models with power structure (combined, power, growth, and exponential) represented significantly less error. However, linear, quadratic, and cubic models showed lower RMSE% and CV contrary to the higher values in R^2.

According to the distribution of cloud points in the figure, the crown diametervariable represents a better fit with the measured biomass than other variables.





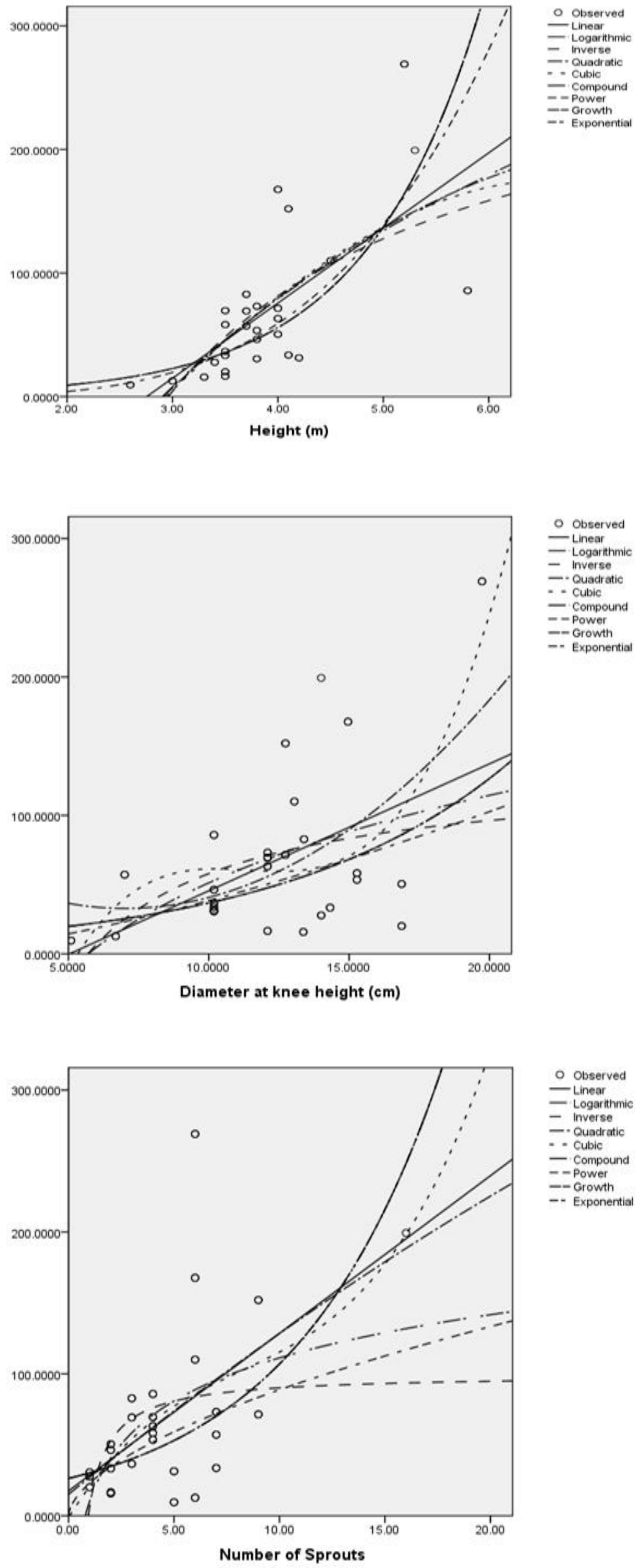


Figure 3. *The distribution of cloud points and fitted curves of 53 samples for estimating tree biomass with five independent variables:crown diameter, diameter ratthe breast height, height, diameter at the kneeheight, and number of sprouts.*

Results of ANN Method in Estimating Above-Ground Biomass

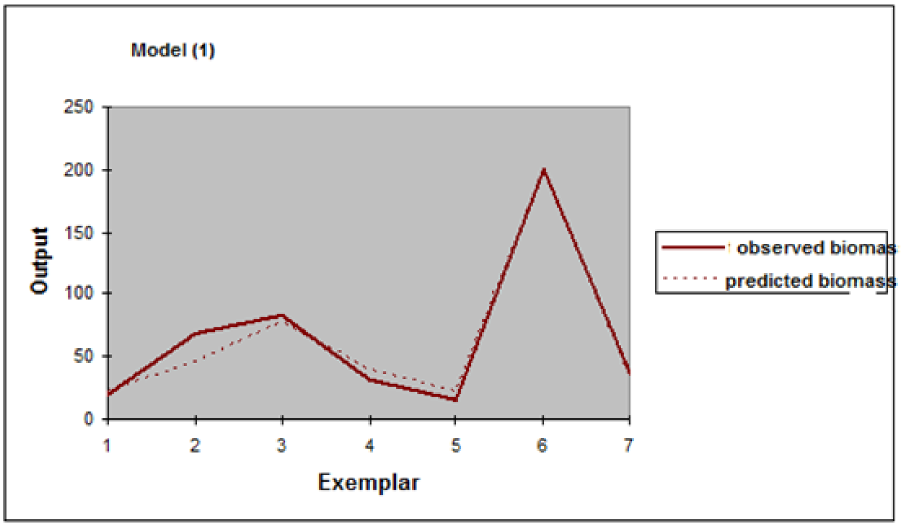
In the present study, 60% of the data in neural networks were allocated for training, 25% for validation, and 15% for network testing. Network estimations were evaluated by MAE, RMSE, and R^2 criteria in the MLP and RBF methods.

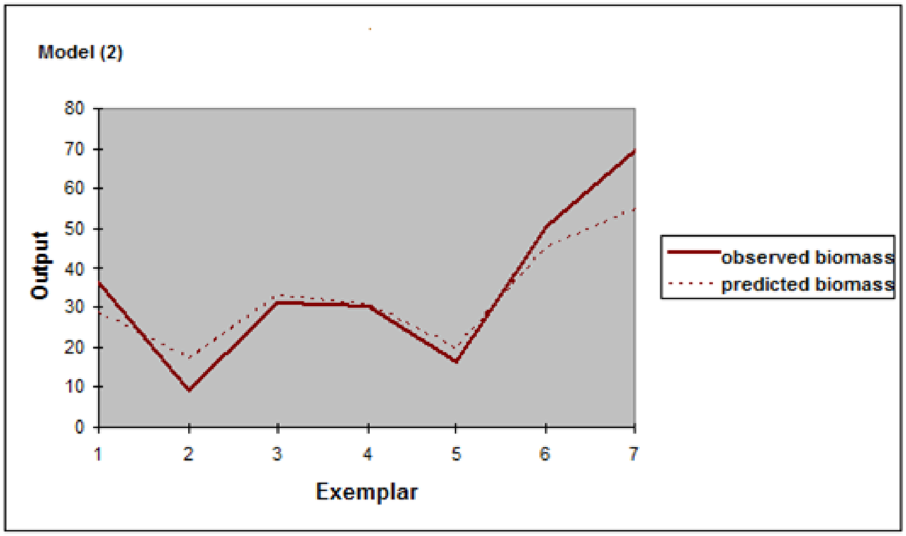
Table 3 presents the performance of both MLP and RBF methods. As seen, the Tanaxon transfer function was used in both methods. Comparing the two approaches reveals that the highest R^2 in the MLP method is related to Model (1) with a variable diameter of crown and Model (4) with variables of crown diameter, diameter at the breast height, height, and diameter at the knee height (R^2 = 0.98). However, in the RBF method, the highest R^2 is obtained by Model (5) with the variables of crown diameter, diameter at the breast height, height, diameter at the knee height, and the number of sprouts (R^2 = 0.96). The RMSE values in Models (1) and (2) in the MLP method were less than RBF, while by adding the variables, the error rate increased in both ways. This result suggests that crown diameter and diameter at the breast height have better efficiency and accuracy in estimating biomass.

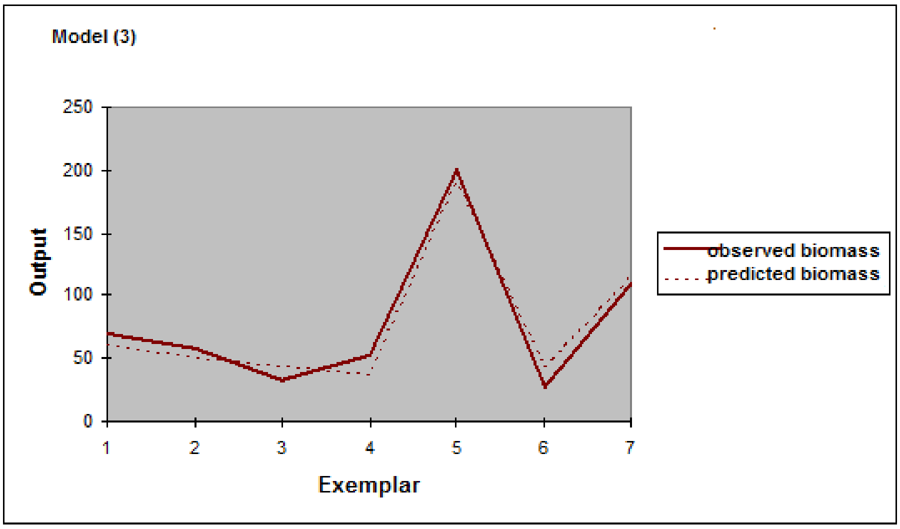
Table 4. *MLP and RBFA assessment in predicting dry tree biomass based on the type and number of input variables.*

Model	Typeof-Network	Independentvariable	Trans-ferfunction	Run	Epoch	RMSE%	CV(RMSE)	MAE%	R^2
1	MLP	CrownDiameter	TanhAxon	3	850	14.4	0.14	10.4	0.98
	RBF	CrownDiameter	TanhAxon	3	800	16.9	0.1	14.9	0.94
2	MLP	CrownDiameter-Diameteratbreast	TanhAxon	3	350	11.6	0.1	9.2	0.96
	RBF	CrownDiameter-Diameteratbreast	TanhAxon	3	750	17	0.15	14.5	0.79
3	MLP	CrownDiameter-Diameteratbreast-Height	TanhAxon	3	850	16.9	0.16	15.9	0.96
	RBF	CrownDiameter-Diameteratbreast-Height	TanhAxon	3	350	20.2	0.2	15.3	0.94
4	MLP	CrownDiameter-Diameteratbreast-Height-DiameteratKnee	TanhAxon	3	500	17.1	0.17	15.4	0.98
	RBF	CrownDiameter-Diameteratbreast-Height-DiameteratKnee	TanhAxon	3	400	17.02	0.17	12.4	0.88
5	MLP	CrownDiameter-Diameteratbreast-Height-DiameteratKnee-NumberofSprout	TanhAxon	3	650	20.64	0.2	17.2	0.88
	RBF	CrownDiameter-Diameteratbreast-Height-DiameteratKnee-NumberofSprout	TanhAxon	3	500	20.76	0.2	18.45	0.96

Comparing the error difference between the measured and predicted values in the MLP (Figure 3) and RBF (Figure 4) neural networks revealed that MLP could predict the observation error well, especially in Models (1) and (2).


Model (1)
250
200
150
100
50
0
Output
1
2
3
4
5
6
7
Exemplar
observed biomas
predicted biomass


Model (2)
80
70
60
50
40
30
20
10
0
Output
1
2
3
4
5
6
7
Exemplar
observed biomass
predicted biomass


Model (3)
250
200
150
100
50
0
Output
1
2
3
4
5
6
7
Exemplar
observed biomass
predicted biomass

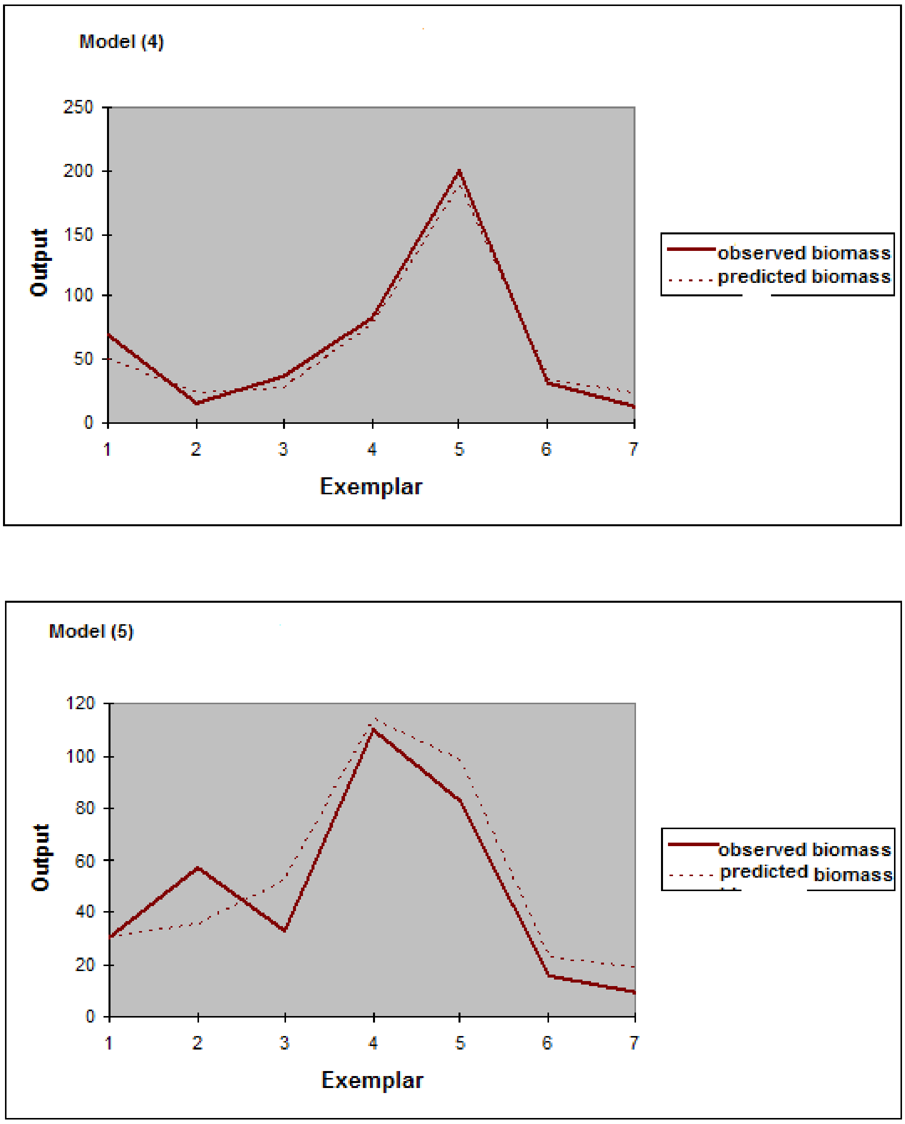
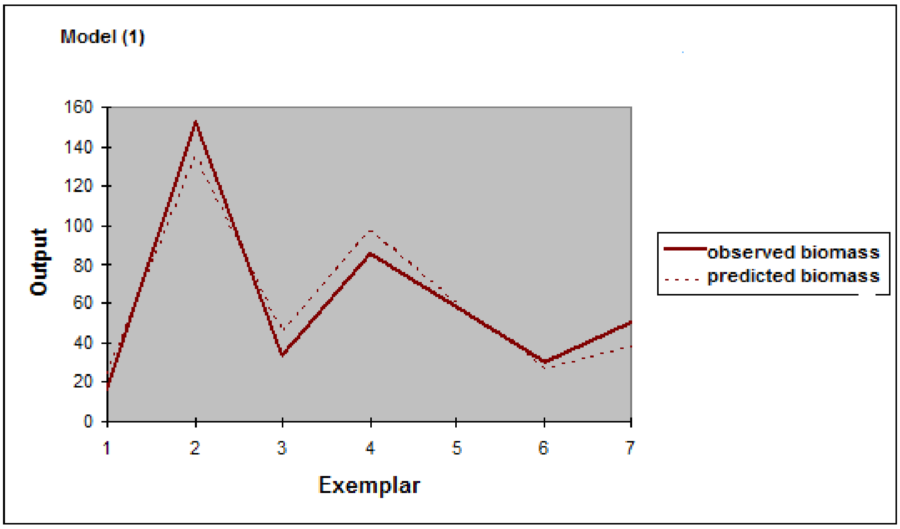
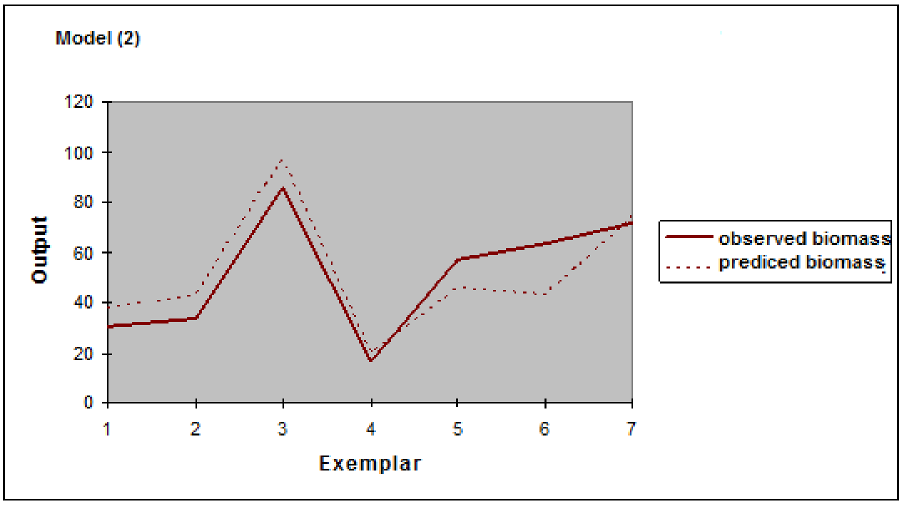
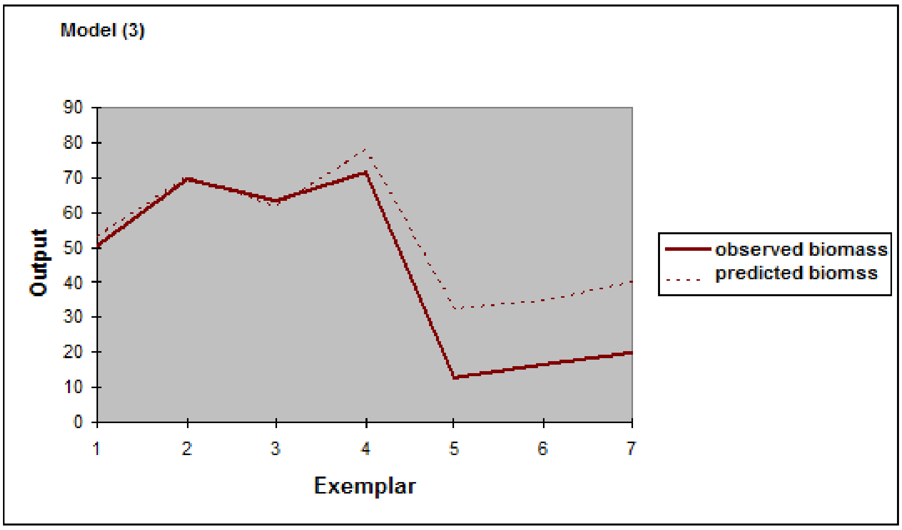
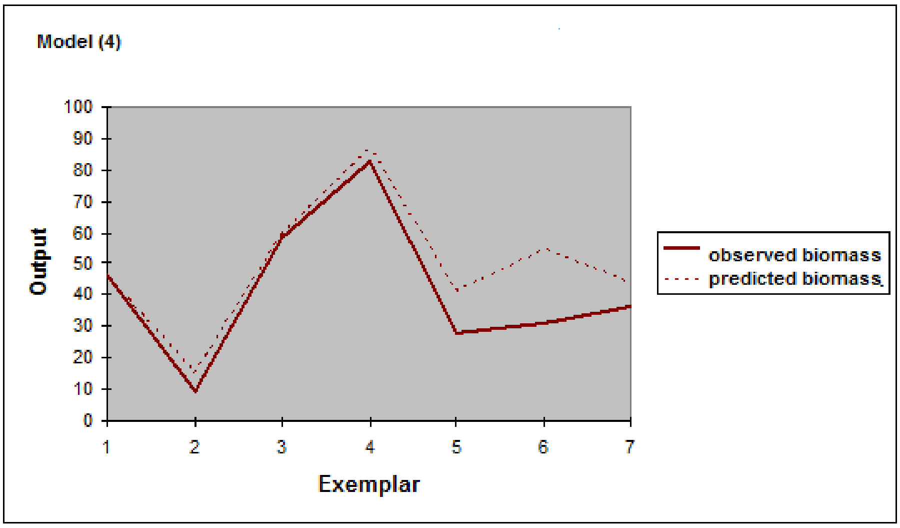


Figure 4. *Comparing error differences between measured and predicted values in the MLP.*




Model (2)
Output
Exemplar
observed biomass
prediced biomass


Model (3)
Output
Exemplar
observed biomass
predicted biomss


Model (4)
Output
Exemplar
observed biomass
predicted biomass

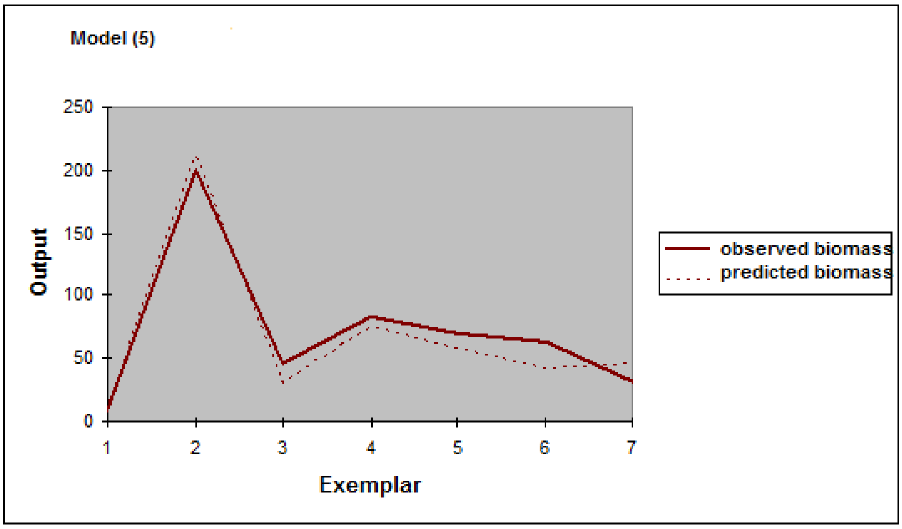


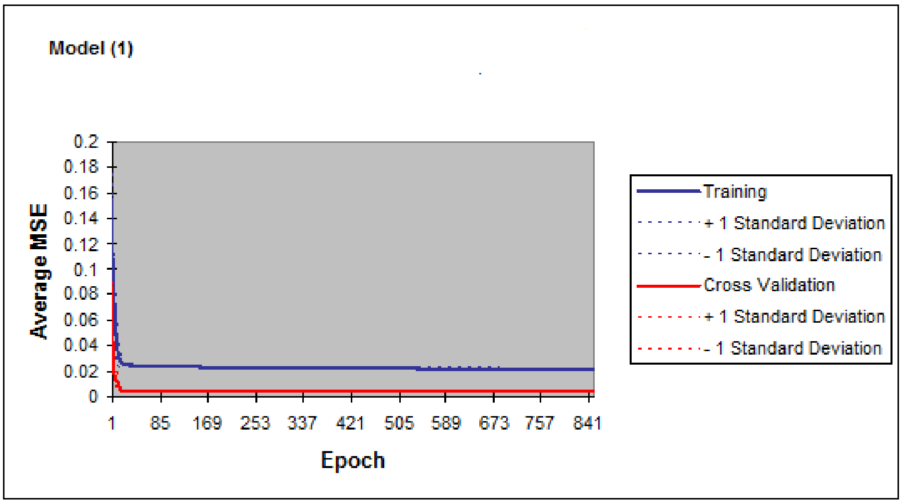
Figure 5. *Comparison of the error differences between measured and predicted values in the RBF neural network.*

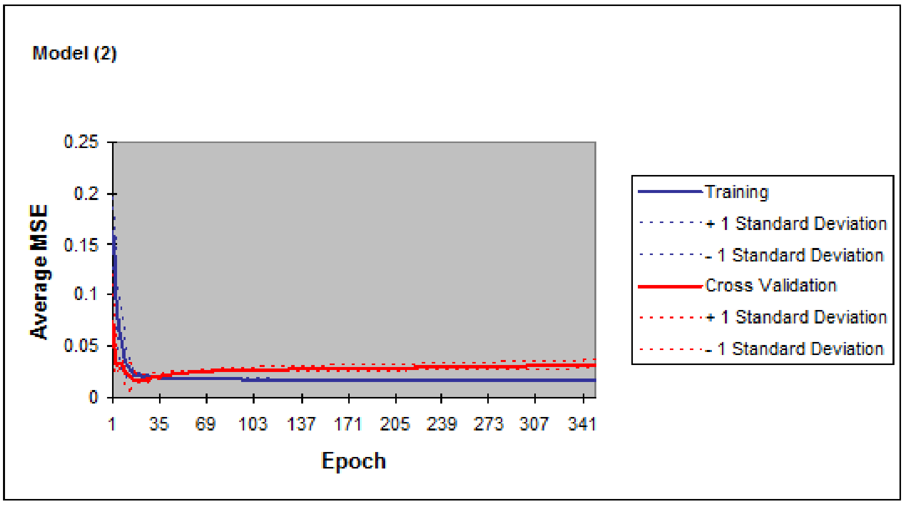
Moreover, the training and validation RMSE values were compared against the epochs (Table 4 and Figures 5 and 6). As can be seen, MLP and RBF methods could significantly lower the RMSE..

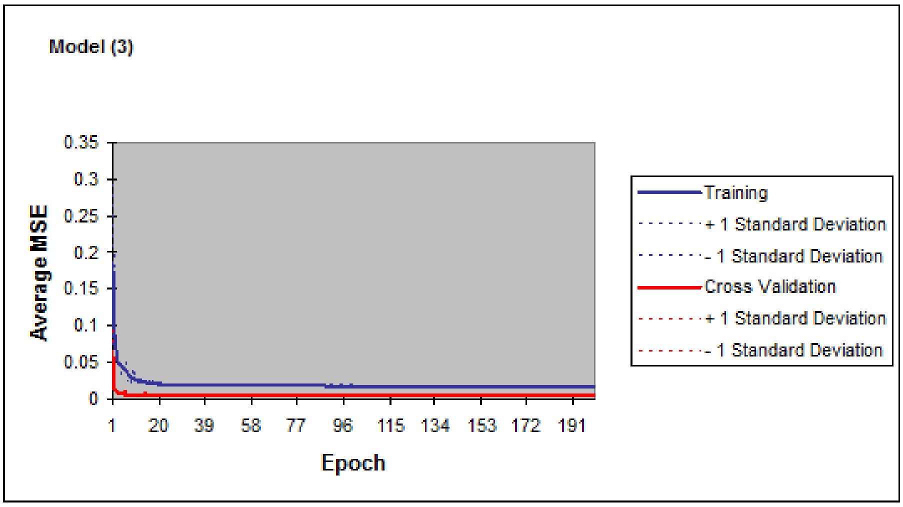
By increasing the number of variables in Model (5) in both MLP and RBF networks, the RMSE% was reduced to 0.06% in the training data set in RBF at epoch 406 and to 0.04 in MLP at epoch 650. Moreover, the validation data set decreased by 0.06% in RBF in epoch 732 in Model (2) and 0.1 in epoch 200 in MLP in Model (3).

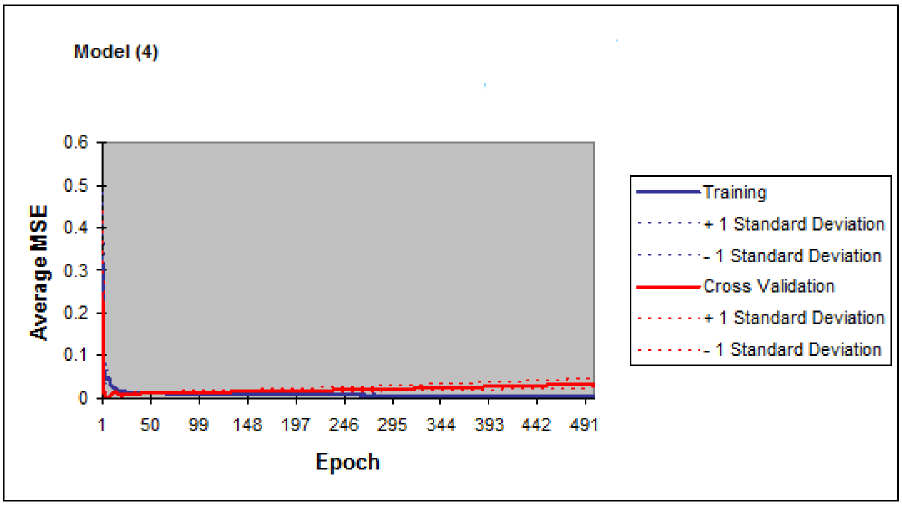
Table 5. *Results of the average square of training error and validation against thenumber of epoch.*

Model	NeuralNetwork	EpochinTraining	EpochinValuation	RMSE%inTraining	RMSE%inValuation
(1)	MLP	850	17	0.21	0.11
	RBF	504	117	0.18	0.31
(2)	MLP	350	14	0.19	0.25
	RBF	740	732	0.15	0.06
(3)	MLP	200	200	0.19	0.1
	RBF	284	278	0.15	0.62
(4)	MLP	500	7	0.12	0.3
	RBF	265	18	0.12	0.33
(5)	MLP	650	9	0.04	0.33
	RBF	406	101	0.06	0.25


Model (1)
Average MSE
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1
85
169
253
337
421
505
589
673
757
841
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation


Model (2)
Average MSE
0.25
0.2
0.15
0.1
0.05
0
1
35
69
103
137
171
205
239
273
307
341
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation


Model (3)
Average MSE
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1
20
39
58
77
96
115
134
153
172
191
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation



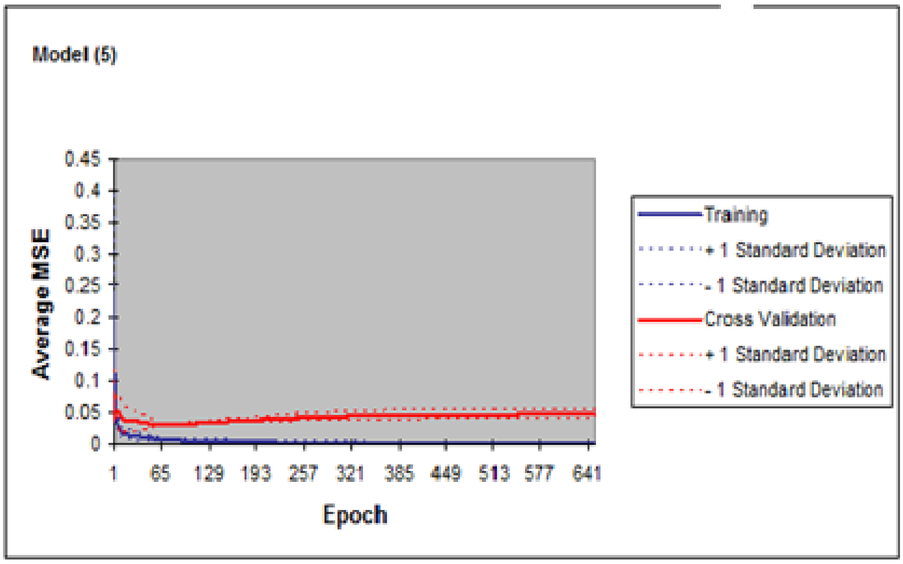
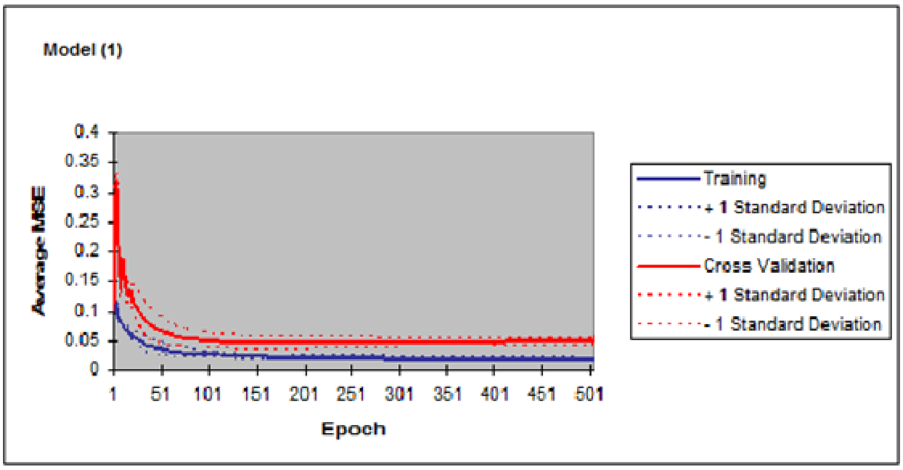
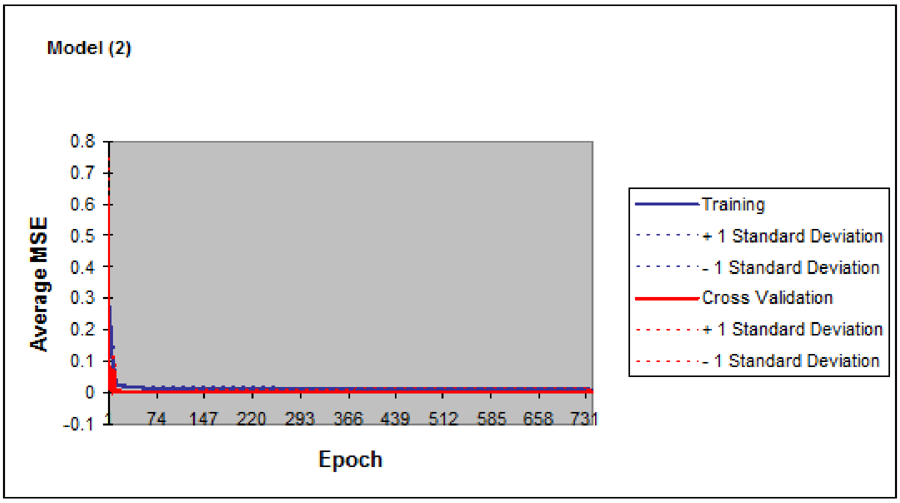
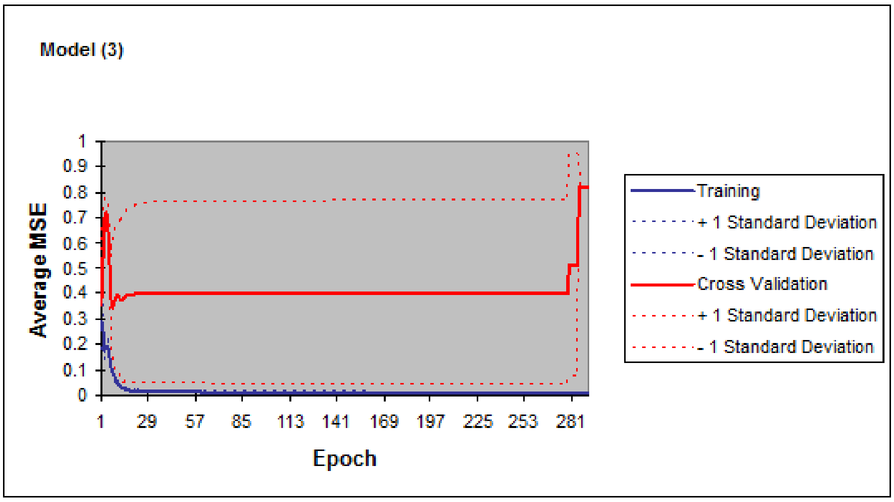
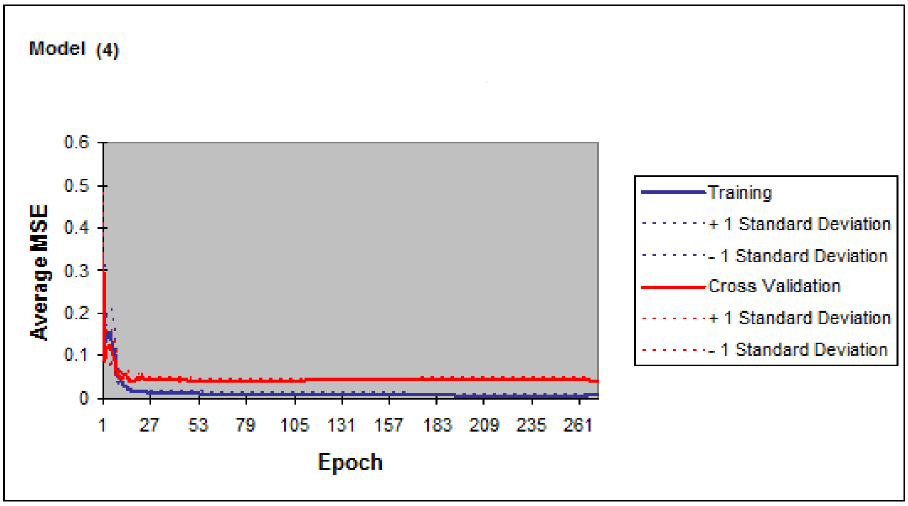


Figure 6. Training and validation RMSEagainst the epoch number in the MLPmethod.




Model (2)
Average MSE
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
1 74 147 220 293 366 439 512 585 658 731
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation


Model (3)
Average MSE
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 29 57 85 113 141 169 197 225 253 281
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation


Model (4)
Average MSE
0.6
0.5
0.4
0.3
0.2
0.1
0
1 27 53 79 105 131 157 183 209 235 261
Epoch
Training
+ 1 Standard Deviation
- 1 Standard Deviation
Cross Validation
+ 1 Standard Deviation
- 1 Standard Deviation

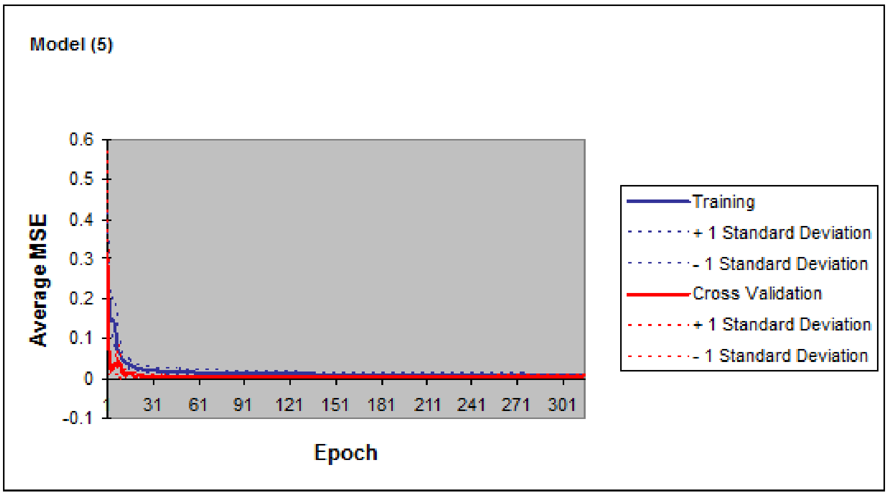


Figure 7. *Training and validation RMSE against the epoch number in the RBFmethod.*

4. Discussion

Estimating tree biomass is a crucial subject in forest management. In this respect, the relationships for these estimates with a minimal error are of great importance. The present study estimated the biomass of oak trees through multivariate, nonlinear regression, and neural network regression methods. The estimations were performed using the variables of crown diameter, diameter at the breast height, height, diameter at the knee height, and the number of sprouts. In most studies, the two variables of diameter at breast and height are considered the main variables in predicting biomass.. However, some researchers believe that prediction accuracy can be enhanced using more detailed variables such as crown diameter, live crown height, diameter at the knee height, and the number of sprouts, or variables related to stand such as dominant height and stand basal area.

It is of note that the best models for biomass estimation should have appropriate accuracy, simplicity, and practicality [43]. Previous studies revealed that various tree parts have different roles in estimating tree biomass.For example, [45] and [17] reported that the trunks of eucalyptus trees in Ethiopian plantations could better predict their biomass. However, [11] concluded that branches could be used to accurately predict the biomass of the *Combretumglutinosum* and *Terminalia laxiflora* species. In this study, the results of linear and nonlinear regression analyses revealed that the crown diameter is the best variable for increasing the R^2, which was also reported in the results of linear regressions [13]. This finding is consistent with those of Forester et al. (2021) [31], who identified crown diameter as a suitable variable to estimate the aerial biomass of eucalyptus trees in the forests of South Australia. This discrepancy in the type of variable in tree biomass prediction can be attributed to the differences in assigning energy resources to different components of trees in other species.

Furthermore, the results showed that multivariate regression methods fit better with the observed biomass (R^2 = 0.823 in model 5) by increasing the variables, including crown diameter, diameter at the breast height, height, diameter at the knee height, and the number of sprouts. Thus, increasing the number of variables increased the R^2 while the RMSE was not highly reduced (40.8%).However, considering the significant reduction in estimation error from calculating RMSE% and CV (RMSE) in power, exponential, combined, and growth equations, these allometric equations can be used to estimate oak tree biomassThis result is inline with [42] results, who identified the power model as suitable for data fitting. It is worth noting that choosing between linear and nonlinear regression models is still controversial [34, 25]. In this respect [44], [19] and [40] associated the selection between linear and nonlinear regression models with the statistical error distribution. They suggested using linear regression models in normally-distributed data but nonlinear models in data without normal distribution [16] believed no difference between linear and nonlinear methods in tree biomass prediction. Indeed, they consider the dominant role of variance deviation from biomass in biomass prediction.

Despite the importance and efficiency of allometric equations in estimating biomass, there is high uncertainty of 20 to 60% in the results of these equations [36]. Complex environmental conditions (e.g., longitude, latitude, and forest structure) are not entirely considered in these models when predicting the daily biomass of trees [8]. Therefore, these equations can be replaced using tools such as ANNs. In the present study, assessing the capability of MLP and RBF neural networks in estimating oak tree oil indicated that these networks can increase the R^2 up to 0.98 in Model (4) of the MLP method and 0.96 in Model (5) of the RBF method.. These values are higher than those of the multivariate regression method (R^2 = 0.823). The essential ability of ANNs is their estimation error reduction. Comparing the RMSE% and MAE% values of the prepared models with those of the regression method revealed a higher error reduction in the prepared models.. However, it is noteworthy that increasing the number of variables in this method increased the R^2, similar to the linear regression method. However, it increased the error such that Models (1) and (2) represented the lowest error while increasing the number of variables. In this respect, the error increased from 11.6% in Model 2 to 20.76% in Model 5. Hence, comparing the outputs of ANN and multivariate regression revealed that the ANN has better accuracy with higher R^2 and more minor prediction error. These results can be attributed to the initial independent assumptions of the ANN regarding the data and because of nonlinear relationships between data, not predicted by the regression.

Moreover, comparing the performance of ANN with nonlinear regression models revealed that R^2 in both MLP and RBF networks was higher than the nonlinear regression models. However, nonlinear models still outperformed in terms of estimation error.These results are consistent with thoseof [42] who modeled the above-ground biomass of mixed beech forests using allometric equations and ANNs..In the study of [31] the ANN yielded more accuracy in predicting the above-ground biomass of *Pinusbrutia* compared to the regression nonlinear equations. However, contrary to these studies, in our work, the error in non-regression methods showed a more significant reduction than in ANNs. According to Table 5, due to the different number of replications in the models, the RMSE of each model was used in addition to the R^2. Considering the same selection range for testing, training, and data validation, a model has a maximum validity when it has an error difference close to the training and data validation in addition to the minimum RMSE) related to the data test [41]. Thus, the ANNs revealed that Model 2 with the crown diameter and diameter variables at the breast height represented better efficiency in estimating the oak trees' biomass.

5. Conclusion

The present study showed a better performance of neural network models than allometric equations in estimating oak biomass in the study area. In this respect, the ANNs estimated the above-ground biomass of the oak trees with better accuracy and much lower error without the limitations of regression methods. Although the number of selected samples in this study is relatively low, this smaller sample size can show a significant estimation difference at higher levels than regression estimations. Thus, it is suggested to use more samples in future studies to obtain more accurate and tangible estimates. Furthermore, explaining the computational models of oak tree biomass using linear and nonlinear models revealed that crown diameter and following diameter at the breast height can be used to estimate the biomass of oak trees. Furthermore, among the regression models, the cubic model had the best conditions in terms of R^2, while the power, exponential growth, and combined models represented a very low RMSE.

Overall, the findings of this study suggest that neural network models can help forest managers and ecologists to gain a better view of AGB changes in the forest.

Abbreviations

MLP	Multi layer Perceptron
RBF	Radial Basis Function
AGB	Aboveground Biomass
RMSE	Root Mean Square Error
ANN	Artificial Neural Network
MAE	Mean Absolut Error
CV	Coefficient of Varriation
SOM	Self-organizing Map
SVM	Support Vector Machine
PCA	Principal Component Analysis

Conflicts of Interest

The authors declare no conflicts of interest.

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