COMPARISON OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM, ARTIFICIAL NEURAL NETWORKS AND NON-LINEAR REGRESSION FOR BARK VOLUME ESTIMATION IN BRUTIAN PINE (*PINUS BRUTIA* TEN.)

ÇATAL, Y.[1*] – SAPLIOĞLU, K.[2]

[1]*Forestry Faculty, Süleyman Demirel University, 32260 Isparta, Turkey*

[2]*Engineering Faculty, Süleyman Demirel University, 32260 Isparta, Turkey*

Corresponding author
e-mail: yilmazcatal@sdu.edu.tr; phone: +90-246-211-3955; fax: +90-246-211-3948

Abstract. The bark is required to determine the volume of bark while identifying tree volume in forest planning. Since the bark volume of brutian pine (*Pinus brutia* Ten.) is considerably more when compared to other tree species, a real-like estimation should be made for the amount of bark. In this study, the Adaptive Neuro-Fuzzy Inference System (ANFIS) method was implemented in the bark estimation. The results obtained with the ANFIS method were compared with the results obtained with the Non-Linear Regression (NLR) and Artificial Neural Networks (ANN) methods. Among the eight models that can be used to determine the bark volume in the NLR method, the Morgan-Mercer-Flodin (MMF) model was determined to be the model giving the best results. Brutian pine bark volume model with the smallest values of the indicators used (MAE = 0.01630; RMSE = 0.02345; FI = 0.955363 and Bias = 0.00151) is the MMF nonlinear model. The amount of bark obtained with the ANFIS method provided better results when compared to ANN and to NLR. The slope graphs for the values estimated with the real value and method for the ANFIS, ANN and NLR methods were found to be 44.01°, 44.60° and 44.83°, respectively. In conclusion, the bark estimation with the ANFIS method provided better results when compared to the ANN and LNR methods.
Keywords: *bark amount, multiple regression, forest inventory, modelling, regression models*

Introduction

The bark thickness of trees is defined as the area remaining in between the cambium layer and the outer limit of the stem. It is very important to determine the amount of bark, as well as the volume of the individual trees. Because, bark appears as the biggest waste material since it does not have a wide usage area in the wood industry. Sometimes, bark constitutes 20% of the tree volume (Laasasenaho et al., 2005; Cellini et al., 2012). At times considered a bothersome waste product, bark is now widely used as an industrial fuel, in soil amelioration, and as ground cover. Bark is also a possible source of chemical feed stocks (Doruska et al., 2009). Today, most pulp and paper mills, plywood plants, and sawmills burn all their bark to produce energy to run the plant and to dry products (Adler, 2007; Bowyer et al., 2007).

The main element in even-aged forest management is growth and yield prediction. Prediction consists in predicting harvest and future growth stocks, which are essential for forest management. It is highly important to estimate in advance the amount of usable wood to be obtained from the forest during the planning stage in forest management. However, the correct determination of the bark amount in an individual tree is one of the most significant components of planning. Furthermore, the amount of

bark volume to be included in the stand simulation models as a variable is an important component for the models to be operated correctly.

The bark volume is generally expressed as a percentage according to the total tree volume. This rate varies by tree species, diameter, total height, age, height on stem, site index, genotypes and similar characteristics (Philip, 1994; Laassenaho et al., 2005). It was determined that different habitats and growing conditions in different coniferous tree species provide different results related to bark thickness (Loetsch et al., 1973; Wilhelmsson et al., 2002; Laasasenaho et al., 2005; Sönmez et al., 2007). There are also differences between the origins of the same tree species (Mc Connon et al., 2004; Kohnle et al., 2012). Thus, it is important to determine bark thickness. The bark thickness and the relationship between the bark thickness and the other tree parameters are investigated by many researchers (Malone and Liang, 2009; Stängle et al., 2017). However, there are a limited number of studies on the bark volume (Laasasenaho et al., 2005; Cellini et al., 2012). There are not a sufficient number of studies on the bark volume of tree species in Turkey (Kahriman et al., 2016).

Linear and non-linear regression models revealing the bark volume are tested (Kozak and Yang, 1981; Diamantopoulou, 2005; Malone and Liang, 2009; Cellini et al., 2012). Due to some prejudices resulting from the method of least squares and the fact that errors in the regression equations may be big, alternative methods are studied (Diamantopoulou, 2005). The most common ones among these methods are Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). A number of researchers have investigated the applicability of ANN models to the field of forest modelling (Zhang et al., 2000; Leduc et al., 2001; Liu et al., 2003; Corne et al., 2004; Leite et al., 2011). There are also studies on forestry with ANFIS (Bui et al., 2012; Pradhan, 2013; Jaafari et al., 2017). It was determined in the previously conducted studies that the ANN method provides better truth results for training and testing data in determining the amount of bark when compared to the regression method (Diamantopoulou, 2005).

Pinus brutia (*Pinus brutia* Ten.) is a pine native to the eastern Mediterranean region. Brutian pine in Turkey is an important tree species, which has a spreading area of 5.6 million hectares. It constitutes 25.1% of the forests in Turkey. Brutian pine stands meet an important part of the wood need in Turkey (GDF, 2015).

The aim of this study is to reveal the method by which the amount of bark in brutian pine trees in Turkey, where it has the widest spreading area in the world, can be determined correctly. Firstly, the appropriate model was determined with Non-Linear Regression (NLR) method among many models. Secondly, the bark volumes found with the ANN and ANFIS methods as an alternative to the NLR method with this model determined were compared, and the method providing the most real-like result was determined.

Materials and methods

Material

Brutian pine trees in the forests of Antalya, Isparta and Burdur regions located in the south of Turkey were measured within the scope of the study *(Fig. 1)*. The study areas is situated between 37°13'49'' N, 29°23'54'' E, to 37°13'49'' N, 31°26'31'' E, average slope 10-25°, predominantly south aspect 600-1000 m altitude. The study area is found

Çatal – Saplioğlu: Comparison of adaptive neuro-fuzzy inference system, artificial neural networks and non-linear regression for
bark volume estimation in brutian pine (*Pinus brutia* Ten.)
- 2017 -

on calcareous formations. The soil is generally shallow or medium-deep, and stony, with a predominantly clay texture.
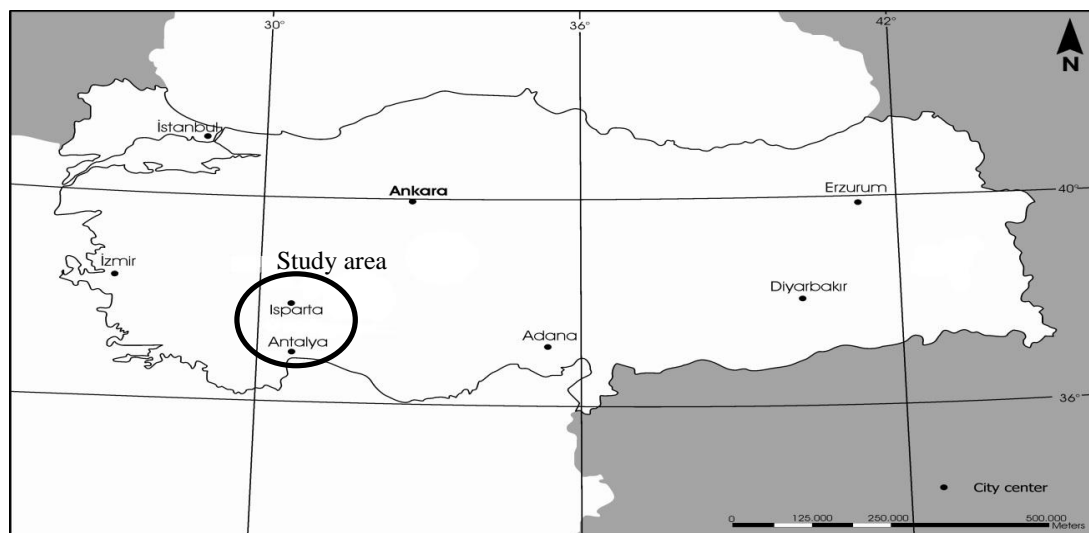
Figure 1. *Location of study area in Turkey*

Six stands were selected to different site quality. The stands have same aged, pure and normal canopy. A total of 338 trees enough to compare statistics were cut, and the following variables were measured: breast height diameter-$d_{1.3}$ (cm), paired data of diameters-d_i (cm) and height-h_i (m) along the stem, total height of the tree-H (m), bark thickness for each d_i and h_i, BT_i (cm). Measures were taken with metric tapes over cut faces of each log, with a precision of ±1 mm.

The cylinder volume and log volume were provided volume by using diameter values with and without bark obtained on the stem, and the volume of each section was provided volume with the Smalian's formula, and the end part was provided volume with the cone volume formula. The total volume of the parts was obtained from the tree volume with and without bark (*Eq. 1;* Avery and Burkhart, 2002; West, 2009).

$$v = \frac{\pi}{4}(d_{0.3}^2)0.3 + \frac{\pi}{4}\left(\frac{d_{0.3}^2 + d_i^2}{2}\right).l_i + \frac{\pi}{4}\left(\frac{d_i^2 + d_{i+1}^2}{2}\right)l_{i+1} + \ldots + \frac{\pi}{4}\left(\frac{d_{n-1}^2 + d_n^2}{2}\right)l_{i+n} + \frac{\pi}{4}\frac{1}{3}d_k^2 l_t \quad \text{(Eq.1)}$$

In the equation π is 3.14159; v_i is the ith volume of the *k* sections of the bole; v_t is the top section volume; $d_{0.3}$, $d_{1.3}$, $d_{3.3}$, …, d_k are diameters at different height and *l*t is the length of the top bole section.

Thus, the tree volume with bark (*v*), tree bark volume (*v_b*) obtained by subtracting tree volume without bark from tree volume with bark, breast height diameter with bark (*d_{1.3}*) and breast height diameter without bark (*d_{1.3u}*) values of a tree were acquired.

Non-linear regression (NLR)

It is required to ensure some preconditions to perform the regression analysis. These conditions are the facts that data exhibit normal distribution, there is a linear relationship between dependent and independent variables, homoscedasticity is provided, there are not multi-colinearity problems, and error terms are independent of

each other (Hair et al., 2009). In this study for the NLR, whether the amount of bark, which was a dependent variable, exhibited normal distribution was tested with the Lilliefors test. It is an improvement on the Kolomogorov-Smirnov (K-S) test-correcting the K-S for small values at the tails of probability distributions-and is therefore sometimes called the K-S D test. Many statistical packages (like SPSS) combine the two tests as a "Lilliefors corrected" K-S test. Unlike the K-S test, Lilliefors can be used when you do not know the population mean or standard deviation. Essentially, the Lilliefors test is a K-S test that allows you to estimate these parameters from your sample (SPSS-Guide, 2010).

Whether variances are distributed homogeneously is tested with Levene's test. Levene's test is used to test if k samples have equal variances. Equal variances across samples are called homogeneity of variance. Some statistical tests, for example the analysis of variance, assume that variances are equal across groups or samples. The Levene test can be used to verify that assumption (Hair et al., 2009). The Durbin-Watson test statistic tests the null hypothesis that the residuals from an ordinary least-squares regression are not auto-correlated against the alternative that the residuals follow an AR1 process (Tabachnick and Fidell, 2014). The Durbin-Watson statistic ranges in value from 0 to 4. A value near 2 indicates non-autocorrelation (Cellini et al., 2012); a value toward 0 indicates positive autocorrelation; a value toward 4 indicates negative autocorrelation (Anderson et al., 2004). The variance inflection factor (VIF) value is a measure of the amount of multicollinearity in a set of multiple regression variables. The presence of multicollinearity within the set of independent variables can cause a number of problems in the understanding the significance of individual independent variables in the regression model. Using variance inflation factors helps to identify multicollinearity issues so that the model can be adjusted (SPSS-Guide, 2010). These preconditions have been tested in this study.

The following commonly used models in forestry were selected for NLR. The Logistic (*Eq. 2*); Gompertz (*Eq. 3*); Mitscherlich (*Eq. 4*); Morgan-Mercer-Flodin (*Eq. 5*); Verhulst (*Eq. 6*); Asymptotic Regression (*Eq. 7*); Richards (*Eq. 8*) models were used for the non-linear regression method to determine the bark volume (Norusis, 2000).

Logistic Model $$v_b = \frac{1}{(1+e)^{-Z}}$$ (Eq.2)

Gompertz Model $$v_b = \beta_0 \exp(-\beta_1 \exp(-\beta_2 Z))$$ (Eq.3)

Mitscherlich Model $$v_b = \beta_0 + \beta_1 \exp(-\beta_2 Z)$$ (Eq.4)

Morgan-Mercer-Flodin Model $$v_b = \frac{\beta_0 \beta_1 + \beta_2 Z^{\beta_3}}{\beta_1 + Z^{\beta_3}}$$ (Eq.5)

Verhultst Model $$v_b = \frac{\beta_0}{1 + \beta_1 \exp(-\beta_2 z)^{\frac{1}{\beta_3}}}$$ (Eq.6)

Asymptotic Regression Model $$v_b = \beta_0 - (\beta_1 * \beta_0^{Z})$$ (Eq.7)

Richards Model $$v_b = \frac{\beta_0}{1 + \beta_1 \exp(-\beta_2 z)^{\frac{1}{\beta_3}}}$$ (Eq.8)

β_0, β_1 refer to the regression coefficients in the equation. *Equation 9* was used to obtain the Z value.

$$Z = \beta_0 + \beta_1 d_{1.3} + \beta_2 d_{1.3u} + \beta_3 v$$ (Eq.9)

The final state of the equations was achieved by including *Equation 9* in the non-linear regression equations. The coefficients of the non-linear regression models were obtained with the NLR module in the SPSS statistics package program. The methods of Norusis (2000) were used for an appropriate initial value.

Artificial neural networks (ANN)

ANN were developed by inspiring from the human brain, and they are the information processing structures connected to each other with the aid of weighted connections (Hotunoğlu and Karakaya, 2011). Each cell has its own memory. The basic logic of the ANN is that it cannot learn by itself. One of the biggest disadvantages of the ANN is the memorization of the system. It can memorize by establishing a relationship between disconnected events given to it. It is required to distinguish the test data to understand whether the system is based on memorization or learning and to test the system with these data after the learning process (Chang et al., 2010). If the learning process is completed successfully, a high statistical relationship is found in the analyses conducted for the test data. However, if a model including a high statistical relationship in training cannot exhibit this relationship to the test, it is not successful. Therefore, a certain part of the data is separated for the test. The operation hierarchy of the system is presented below in a graph (*Fig. 2*).
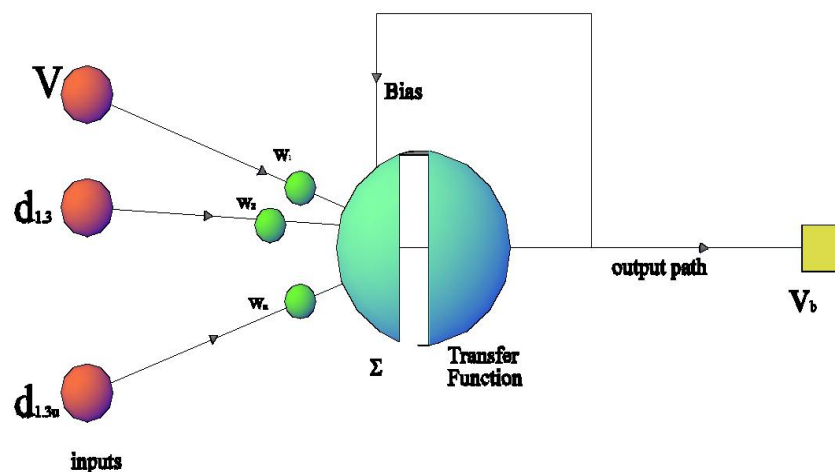

Figure 2. ANN operation sequence diagram

Inputs: They are the information sent from outside to an artificial cell. They are determined by the user. *Weights:* They are used to determine the significance level of

the incoming information. They are reassigned by being rearranged in return for each error during training. *Addition function:* This function calculates the net incoming input to a cell. This operation can be performed with many different functions. The most common one is the weighted addition. Each incoming information is found by multiplying it by its weight (Geem and Roper, 2009). Activation Function: It determines the output in return for the incoming input. In general, a non-linear function is selected. An easy differentiation of the function is extremely important in terms of the speed of the process due to the use of the activation function derivative, especially in feed-back networks. Sigmoid functions are the most common functions.

The feed forward back propagation learning algorithm was used in the operation of the model in question. This algorithm consists of two steps. The first one is the feed forward step that forwards the external information input in the input cells to calculate the output information in the output units. The second step is the back propagation of the differences between the values calculated in the output unit and the observation values. The hidden layer output expression in the hidden layers in artificial neural networks is calculated as in *Equation 10* (Partal et al., 2008).

$$y_j = f\left(\sum x_i W_{ij}\right) \qquad \text{(Eq.10)}$$

Here, each neuron is multiplied by the weights of the input signals and summed up. Here, *f* is the activation function used in hidden and output layers, and its expression is indicated in *Equation 11*.

$$f_j = \frac{1}{1 + e^{-x_j}} \qquad \text{(Eq.11)}$$

The square of the difference between the required value of the output neuron and the real value provides the *E* error value. The expression of the *E* error value is indicated in *Equation 12*.

$$E = \frac{1}{2} \sum_i (y_i - d_i)^2 \qquad \text{(Eq.12)}$$

The amounts of bark were determined with ANN with these sequences of actions

Adaptive neuro-fuzzy interface system (ANFIS)

ANFIS, developed by Jang (1993), only minor applications of landslide-related studies have been reported (Bui et al., 2012). ANFIS is a multilayer feed-forward network, in which each node performs a particular function on incoming signals and has a set of parameters pertaining to this node (Jang, 1993). ANFIS combines fuzzy logic and ANNs by using the mathematical properties of ANNs in tuning a rule based fuzzy inference system that approximates how the human brain processes information (Akib et al., 2014). The multiplicity and homogeneity of the data are extremely important for the results of the model to operate. The cluster types and number of the data may vary by the type and complexity of the problem (Dongkyun et al., 2018). Each input parameter is introduced to the system (*Fig. 3*).
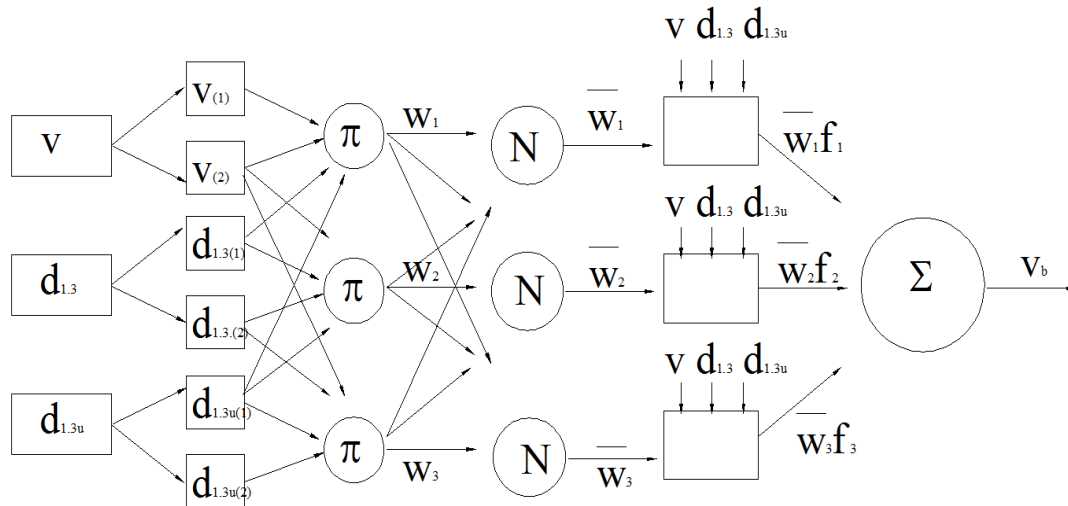
Çatal – Saplioğlu: Comparison of adaptive neuro-fuzzy inference system, artificial neural networks and non-linear regression for
bark volume estimation in brutian pine (*Pinus brutia* Ten.)
- 2021 -

Figure 3. *ANFIS operation sequence diagram*

The cluster number for these parameters introduced is determined. In the next step, weight values are assigned to each input parameter, and they are multiplied. The outputs obtained are sent to the total function, and the errors are determined. These operation steps are repeated until the errors are minimized.

Comparison of methods

Comparison of estimation of methods was based on graphical and numerical analysis of residuals and five goodness of fit statistics: mean absolute error (MAE) (*Eq. 13*), which expresses the average of absolute errors between forecast and actual value; root mean square error (RMSE) (*Eq. 14*), which analyses the precision of estimations; fix index (FI) (*Eq. 15*), which reflect the total variability that is explained by the model considering the total number of parameters to be estimated; mean error (Bias) (*Eq. 16*), which average error for estimated values. The best regression yielded the smallest MAE, RMSE, Bias and the largest FI. These evaluation statistics are defined as:

Mean absolute error
$$MAE = \frac{\sum_{i=1}^{n}|v_i - \hat{v}_i|}{n}$$
(Eq.13)

Root mean square error
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(v_i - \hat{v}_i)^2}{n-k}}$$
(Eq.14)

Fit Index
$$FI = 1 - \left[\frac{\sum_{i=1}^{n}(v_i - \hat{v}_i)^2}{\sum_{i=1}^{n}(v_i - \overline{v}_i)^2}\right]$$
(Eq.15)

Mean error
$$Bias = \frac{\sum_{i=1}^{n}(v_i - \hat{v}_i)}{n}$$
(Eq.16)

where v_i = observed bark volume, $\hat{v}_i$ = predicted bark volume, $\bar{v}$ = mean of observed bark volume, n = number of observations in dataset and k = number of estimated parameters.

Results

The data measured are randomly divided into two sets by ANN. The method application was performed with the training data, and the consistency of the results of the process applied with the testing data was determined. While training data are randomly selected, attention has been carried out for the maximum and minimum data which should be situated in these data. The training data consisted of 221 trees (65%), and the testing data consisted of 117 trees (35%). Training and testing data were compared with t-test (t value = 0.012). With use of a two-tailed t-test for independent two samples, there was not significant difference between the training and testing data (p > 0.05). The summary of the training and testing data is presented in *Table 1*.

Table 1. *Some statistics for the training and testing data*

	Training data (n = 221)				Testing data (n = 117)			
	$d_{1.3}$	$d_{1.3u}$	v	v_b	$d_{1.3}$	$d_{1.3u}$	v	v_b
Minimum	5.3	4.4	0.010	0.004	10.2	8.5	0.040	0.006
Maximum	60.9	49.7	2.795	0.553	49.0	42.5	2.291	0.422
Mean	25.7	21.0	0.680	0.136	23.4	19.5	0.580	0.113

In *Table 1*, $d_{1.3}$ = diameter of breast height diameter (cm), $d_{1.3u}$ = breast height diameter without bark (cm), v = the tree volume with bark (m³), v_b = tree bark volume (m³).

For the NLR, whether the amount of bark, which was a dependent variable, exhibited normal distribution was tested with the Lilliefors test. Since the variance and average of the population were not known, the Lilliefors test and the normality test were conducted. Since the test statistics were found to be 5.246 (p < 0.001), the data were distributed homogeneously. Whether variances were distributed homogeneously was tested with Levene's test, and it was determined that the variances of the data were distributed homogeneously (4.164; p < 0.001). The Durbin-Watson value was found to be 1.987 in this study. This result indicates that there is not auto-correlation between the error terms of the independent variable. The variance inflection factor (VIF) value is required to be less than 10 to be able to test the multi-colinearity problem (SPSS-Guide, 2010). The VIF values were found to be less than 10 in this study.

According to the results obtained for *Equations 2-8* with the non-linear regression analysis, the results obtained as a result of the comparison made by using real values and regression analysis values are presented in *Table 2*.

Çatal – Saplıoğlu: Comparison of adaptive neuro-fuzzy inference system, artificial neural networks and non-linear regression for
bark volume estimation in brutian pine (*Pinus brutia* Ten.)
- 2023 -

Table 2. *The results obtained according to the regression equations*

Eq. no	MAE	RMSE	FI	Bias
2	0.03456	0.03480	0.92541	0.00223
3	0.02856	0.03258	0.93012	0.00302
4	0.02723	0.37820	0.93125	0.00285
5	0.01630	0.02345	0.955363	0.00151
6	0.02856	0.03152	0.91021	0.00278
7	0.03256	0.04023	0.89012	0.00326
8	0.04450	0.05321	0.87202	0.00365

For the eight nonlinear equations of *Table 2,* the range of the MAE values are 0.0163-0.05125 m^3, and the range of the RMSE are 0.02345-0.05562 m^3, the range of the Bias values is 0.00153-0.00455 m^3 with the lowest values for the nonlinear model of *Equation 5*. The range of the FI values is 0.959363-0.851251 with the highest values for the nonlinear model of *Equation 5* too.

$$v_b = \frac{\beta_0\beta_1 + \beta_2\left(\beta_4 + \beta_5 d_{1.3} + \beta_6 d_{1.3u} + \beta_7 v\right)^{\beta_3}}{\beta_1 + \left(\beta_4 + \beta_5 d_{1.3} + \beta_6 d_{1.3u} + \beta_7 v\right)^{\beta_3}} \quad \text{(Eq.17)}$$

The coefficients for *Equation 5,* which is the most appropriate model, were found to be β_0:30.97118; β_1:-8.84891; β_2:26.88242; β_3:4.92827; β_4:0.00635; β_5:-0.00760; β_6:0.08300; β_7:1.45622.

The real bark volume values and the estimated volume values were compared with four evaluation criteria for three methods used in the determination of the amount of bark in an individual tree (*Table 3*).

The actual measured values of the brutian pine bark volume were compared to the corresponding values predicted by the all methods. Results are given in *Table 3* and also the comparisons were made with the help of paired t-test, 45° line test.

Table 3. *The evaluation criterion values obtained for the NLR, ANN and ANFIS methods*

Methods	MAE	RMSE	FI	Bias	Slope (°)	t-Value
NLR	0.01630	0.02345	0.955363	0.00152	44.60	1.525
ANN	0.01077	0.01537	0.971205	0.00125	44.84	1.124
ANFIS	0.00838	0.01157	0.988612	0.00046	44.91	0.852

The values of estimation errors for NLR, ANN and ANFIS in the testing data sets were 0.00152, 0.00125 and 0.00046 m^3, respectively. This shows that the ANFIS model of *Table 3* gave an estimation error that was 1.2 times smaller than the ANN model and was 3.3 times smaller than the best nonlinear model (*Eq. 17*).

The brutian pine bark volume estimates by the NLR model of *Equation 17*, by the ANN model and by the ANFIS of versus measured values for the training and testing data set are shown in *Figure 4a-f*, respectively. The proximity of each point to the 45° line throughout the range of the measured bark volume (*Fig. 4a-f*) indicates that the

Çatal – Saplioğlu: Comparison of adaptive neuro-fuzzy inference system, artificial neural networks and non-linear regression for
bark volume estimation in brutian pine (*Pinus brutia* Ten.)
- 2024 -

ANFIS model is more accurate compared to the NLR model and the ANN model for
test data (*Fig. 4b, d, f*).

As seen from *Figure 4,* it was observed that the real and estimated values in the
graph obtained for the model and test data provided more distributed results when
compared to the NLR method. The ANFIS method provided the best result graphically.
The test values of slope were also calculated and respectively were found equal to
44.01°, 44.60° and 44.83°. The training values of slope were also calculated and
respectively were found equal to 44.60°, 44.84° and 44.91°.
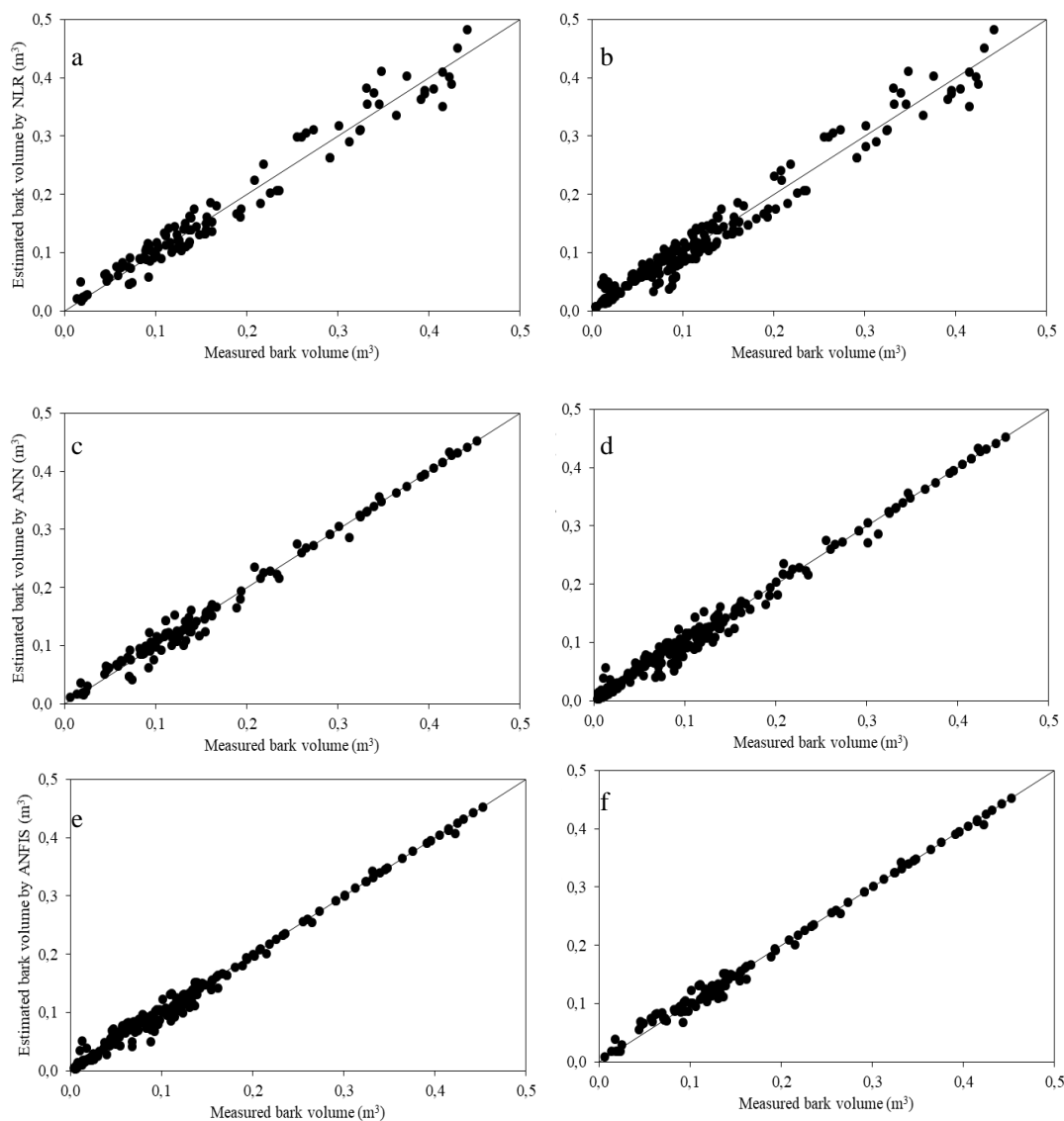
Figure 4. *The amounts of bark volume obtained with the NLR (a-training, b-testing), ANFIS
(c-training, d-testing) and ANN (e-training, f-testing) methods corresponding to the real
volume values*

The estimated volume value and actual volume values obtained with ANFIS, ANN
and NLR methods were compared with the paired samples t test. The t-values were
found to be 1.525, 1.124 and 0.852, respectively. The computed t-values for the NLR,

ANN and ANFIS model were less than the table t-value (1.96 for $\alpha = 0.05$). According to results difference was not found between actual values and estimated values for each of this tree methods.

Discussion

Bark volume depends on its thickness and stem diameter. These variables are being affected by tree age and stand conditions because of diameter of breast height increases (Laasasenaho et al., 2005; Sönmez et al., 2007; Kahriman et al., 2016). However, measuring the parameters of the stands is time consuming. Therefore, parameters that can be easily measured are needed. Linear and non-linear regression models with easily measured variables are used to estimate bark volume (Laasasenaho et al., 2005; Cellini et al., 2012). Due to some prejudices resulting from the method of least squares and the fact that errors in the regression equations may be big, alternative methods are studied. The most common ones among these methods are ANN and ANFIS. But, the use of these methods in forestry is limited. It was determined in the previously conducted studies that the ANN method provides better truth results for training and testing data in determining the amount of bark when compared to the regression method (Diamantopoulou, 2005).

In this study, it was determined that ANFIS method shown better results from ANN and NLR when the variables the tree volume with bark (v), breast height diameter with bark ($d_{1.3}$) and breast height diameter without bark ($d_{1.3u}$) values of a tree which are easy to measure during forest inventories were used in tree bark volume (v_b) estimation. This was followed by ANN and NLR, respectively. Although prediction of the tree bark volume with ANFIS is a complex process requiring specialized, it will be possible to obtain more accurate results by using in forestry. In additional, using the variables the tree volume with bark, breast height diameter with bark and breast height diameter without bark values of a tree measured from the tree, the tree bark volume can also be calculated with sufficient accuracy by the NLR method. For the NLR method, the nonlinear model of Morgan-Mercer-Flodin model was found as the best model. Diamantopoulou (2005) obtained the same equation as being the most appropriate regression equation among the previously conducted studies.

Conclusion

There is not a direct method of measurement for the determination of the bark volume on trees. Alternatively, the amount of bark is tried to be estimated with various methods. In this study, an appropriate regression equation (NLR method) was selected for the estimation of the tree volume with bark, double bark thickness values and the bark volume that is the tree parameter derived from these values, and the bark estimation was made with the ANN and ANFIS methods. The methods were compared as a result of this estimation.

As a result of this study, the bark volume can be obtained more correctly with the ANFIS modelling method. Together with the fact that the ANFIS method used becomes widespread in the forestry studies to be conducted, more realistic results can be obtained in the modelling of forest resources and stand developments.

Çatal – Saplıoğlu: Comparison of adaptive neuro-fuzzy inference system, artificial neural networks and non-linear regression for
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- 2026 -

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