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Relations Between The Productivity Of Turkish Red Pine In Mersin Region And Some Topographic Factors

Emre Kuzugüdenli
Forestry Department
Isparta University of Applied Sciences
Isparta/TURKEY
emrekuzugudenli@isparta.edu.tr

Canpolat Kaya
Forestry Department
Isparta University of Applied Sciences
Isparta/TURKEY

***Abstract*— In this study, it is aimed to determine some topographic factors affecting the productivity of Turkish red pine (*Pinus brutia Ten.*) stands spread in Mersin region and to investigate the mutual relations of these factors with productivity. As a result of this study related to modeling the productivity of Turkish red pine, it was determined that the predictive power of the model obtained by factor analysis is higher than the predictive power of the models obtained by ANN methods.**

Keywords—Turkish red pine, Productivity, Bonitet Index

I. Introduction

Turkey about 13 million hectares of forests are productive fields. Approximately 10 million hectares have degraded [1]. These degraded areas can be brought into forestry by determining the appropriate species that can be used in these areas. Turkish red pine (*Pinus brutia* Ten.) are preferred for use as a rapid growth in Turkey and the timber industry [2]. However, the fact that it has functions such as carbon capture, erosion prevention and rehabilitation, recreation and wildlife has made Turkish red pine a preferred method in afforestation works.

In afforestation studies, it is necessary to determine potential places with good bonitets and to prioritize existing areas with high productivity in natural regeneration works. The determination of potential places where Turkish red pine can be productive can be done by ecological studies on the productivity of the species.

In this study, it is aimed to determine some topographic factors affecting the productivity of Turkish red pine stands spread in Mersin region and to investigate the mutual relations of these factors with productivity.

It was carried out to predict efficiency with Artificial Neural Networks (ANN) technique, which is an application based on artificial intelligence, and to compare the results with the results of factor analysis.

Factor analysis is a statistical method used to determine the cumulative effect of independent variables on dependent variables. ANN, an artificial intelligence application that gives successful results in modeling complex relationships, has been preferred by many scientists today. ANN finds widespread use in many fields (electronics and communications, industry, mechatronics and aviation, etc.) [2]. proceedings. Margins, column widths, line spacing, and type styles are built-in; examples of the type styles are provided throughout this document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

II. Materials and Methods

The study area is located between Mersin region 33 ° - 35 ° east longitudes and 36 ° - 37 ° north latitudes. Karaman and Konya provinces in the north of the study area, Adana in the east and Antalya in the west. One of the forest tree species showing the largest distribution in the region is Turkish red pine. The study area is located in the Mediterranean region and has typical Mediterranean climate characteristics with hot and dry summers and mild and rainy winters [3].

Data were obtained from the thesis carried out by Şahin (2015) [4]. Before analyzing, it was checked whether these data were normally distributed. Various normality control methods are used to determine the conformity of the data to normal distribution. One of the most common of these methods is the examination of skewness-kurtosis values. In this study, the kurtosis-skewness method was used to determine the compliance of variables to normal distribution [5].

Artificial neural networks are a mathematical modeling method developed inspired by the functioning of the human brain. The models are obtained by some computer software that takes the communication principle between neurons, which are human brain cells, as an example [6]. In the ANN model, there are layers with interrelated nerves (Figure 1). These layers consist of three basic groups as input layer, hidden layer and exit layer [7].

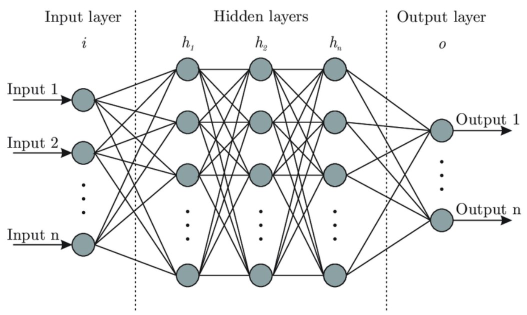

Fig. 1. Artificial neural network structure

The way neurons are connected to each other, activation function and learning rules have led to the formation of various ANN structures. Basically, these structures are divided into 3 basic classes: feedback neural networks, feed forward neural networks and radial-based neural networks. Of these structures, feedback neural networks are more preferred due to their success in prediction and classification processes [6]. In the application of ANN, which includes different neural structures, firstly, input variables and output variables are defined in the system to be predicted and with these definitions, ANN analyzes the data and estimates the weights in a way that will optimize the success in the prediction and minimize the error. This process is called network training in the literature on ANN. With ANN, many different weight values are derived, and by using these weight values, output estimates are obtained with addition and activation functions. The process is completed at the point where the errors are minimum and the changes related to the errors are fixed by analyzing the variation of the errors calculated according to the observation values related to the output variable defined at the beginning with the predicted values obtained by ANN [8].

Artificial neural network performance and accuracy can be improved with some normalization methods applied to ANN data [9]. Various normalization methods are used by researchers, and the Min-Max method is mostly preferred (Equation 1). With Min-Max normalization, the negative effects of extremely large and small data on the model are reduced by scaling the data between 0 - 1 [10].

III. RESULTS

Correlation analysis was carried out in order to determine the mutual relations between the productivity of red pine stands and some topographic factors spread in Mersin region. As a result of the analysis, statistically significant but low correlation relationships were found (Table I).

Table I. Correlation Analysis Results

Variables	***Elevation***	***Slope***	***Aspect***	***Bonitet Index (BI)***
Elevation	1	.085	-.056	**.161****
Slope	.085	1	-.027	**.236****
Aspect	-.056	-.027	1	-.005
Bonitet Index(BI)	**.161***	**.236****	-.005	1

As a result of the analysis, it was determined that the effects of variables alone on BI were insufficient, and Factor Analysis was performed to determine the collective effect of variables on BI. According to the results of the factor analysis, 2 components with a variance value of 10% with a rate of participation in variance greater than 1 were created. Considering the rate of participation of the components in the variance, the rate of participation of the first component in the variance is 33.4% and the value of participating in the variance is 1.34; The rate of participation of the second component in the variance was 25.21% and the value of participating in the variance was determined as 1.01 (Table 2).

Table II. Total Variance Explained

Component	***Total***	***% of Variance***	***Cumulative %***
1	1.336	33.402	33.402
2	1.008	25.210	58.612
3	0.910	18.626	81.374

According to the obtained component matrix, it is seen that the component with the highest BI value correlation value is the 1st component (0.74). It was determined that the correlations of the elevation (0.55) and the slope (0.67) variables were high according to the variables in the 1st component and these 2 variables affect BI (Table 3).

Table III. Component Matrix

	COMPONENT	
VARIABLES	**1**	**2**
Elavation	.553	-.255
Slope	.674	.202
Aspect	-.158	.928
BI	.742	.204

In order to determine whether Aspect, Elevation, Slope and Bonitet Index variables are normally distributed, kurtosis-skewness values were determined. When the skewness-kurtosis values are between -1.5 and 1.5, it is accepted to be a normal distribution [11]. According to these results, it is seen

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that the data obtained show a normal distribution (Table 4).

Table IV. Skewness-Kurtosis Values

Variables	Skewness	Kurtosis
BI	-0.26	-0.38
Slope	0.04	-1.36
Elavation	0.24	-1.27
Aspect	1.3	1.5

After the factor analysis, the estimation phase was started with ANN. In order to determine the relationship between variables, Aspect, Elevation, Slope as input variables, Bonitet Index variable as output. 162 of the data set of 216 sample areas were randomly selected as training and 54 as test data set. Before starting the training of artificial neural networks, Min-Max normalization was applied to all data.

2 artificial neural network models were created with the training data, and these models consist of 3 input 2 layers 10 neurons (2K10N), 3 input 5 layers 10 neurons (5K10N) and the graphics of the models are presented in Figures 2 and 3.

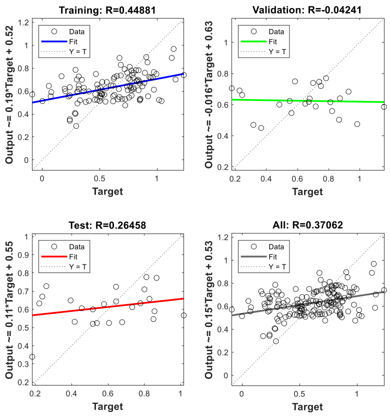

Fig. 2. ANN structure with 2 layers-10 neurons and training graph

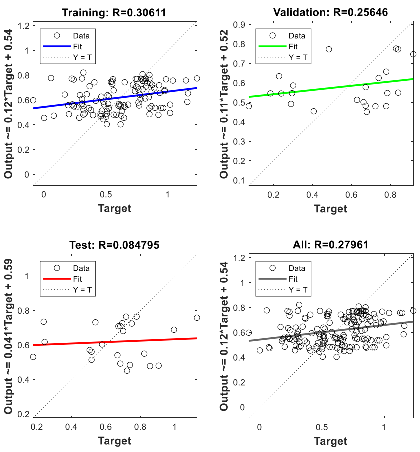

Fig. 3. ANN structure with 5 layers-10 neurons and training graph

Bonitet Index estimates for these 2 models were obtained with the test data set. When looking at the predictive power of the model created with 2 layers of 10 neurons, the R^2 value was determined as 0.16 (Figure 4).

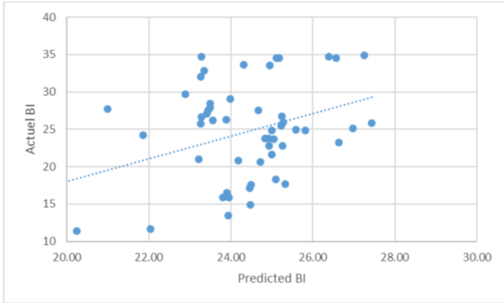

Fig. 4. Relationship of actual and predicted bonitet index for 2 layers-10 neurons

Looking at the predictive power of the model created with 5 layers of 10 neurons, the R^2 value was determined as 0.06 (Figure 5)

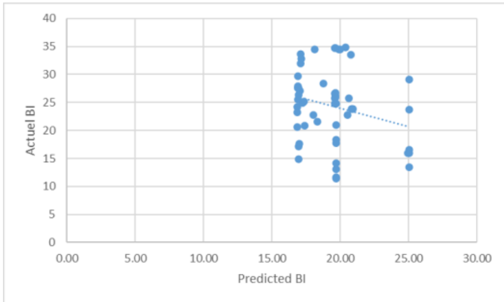

Fig. 5. Relationship of actual and predicted bonitet index for 5 layers-10 neurons

In this study, it is aimed to determine some topographic factors affecting the productivity of Turkish red pine stands spread in Mersin region and to investigate the mutual relations of these factors with productivity.

For this purpose, factor analysis and ANN technique, which is an application based on artificial intelligence, was used and the results obtained were compared. Correlation analysis was performed to determine the bilateral relationships between variables. As a result of the correlation analysis, when the bilateral relationships of the variables with each other are examined, it was found that the variables do not have high correlation with BI. Therefore, factor analysis was conducted to determine the cumulative effect of variables on BI. As a result of the factor analysis, it was determined that Elevation and Slope together have an effect on BI.

After the factor analysis, the estimation phase was started with ANN. In order to determine the relationship between variables, Aspect, Elevation and Slope as input variables are selected as Bonitet Index as output variables. With ANN, 2 models consisting of 2 layers of 10 neurons and 5 layers of 10 neurons were created. Considering the predictive power of these models, R^2 value of 2K10N was determined as 0.16 and R^2 value of 5K10N was determined as 0.06.

In this study related to modeling the productivity of Turkish red pine, it was determined that the predictive power of the model obtained by factor analysis is higher than the predictive power of the models obtained by ANN methods.

IV. DISCUSSION AND CONCLUSION

While determining the potential afforestation areas of Turkish red pine, the decision should be made according to the information obtained from the factor analysis. In other words, areas with high slope and elevation should be given priority. During the vegetation period of Turkish red pine in the region, water deficit occurs in the soil. For this reason, the increase in rainfall depending on the altitude caused the height growth to increase with the elevation. In addition, the increase in altitude will cause a decrease in temperature, decrease in evaporation and the formation of more humid habitats [12].

Higher predictive power can be obtained by adding other site variables not used in this study to the models and retesting.

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