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Modeling and forecasting of dry bean yield in Turkey using Artificial Neural Networks and Time Series Analysis

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Abstract:*The objective of this study is to show that production design may be performed using artificial neural networks (ANN) and time series analysis (Box-Jenkins) in the establishment of dry beans production amount model and in forecasting in Turkey by years.*
In the development of ANN and time series analysis, parameter of years was used as an input parameter and production amount was used as an output parameter. The efficiency of the model developed was determined using statistical parameters such as Mean Squared Error (MSE) and Mean Absolute Error (MAE).The results show that dry bean production will have a fluctuating course in production from 2019 to 2025.
It was observed that ANN models gave better results than time series analysis in dry bean production prediction.
Keywords:*Artificial neural network, time series analysis, production, dry beans.*

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I. INTRODUCTION

Legumes are the second crop group after grains in the world in terms of cultivation area and yield. Although its production has spread around the world including Latin America, Africa, Middle East, China, Europe, USA and Canada, the most produced product is dry beans. Cultivation areas of dry beans were around 25 million ha between 1980-2000; this figure has reached 29 million hectares with an increase of 11% in the last decade [1]. In Turkey, dry bean has an important role in the economic livelihood of rural areas. Dry bean cultivation areas account for 11% of legume growing in Turkey, and ranks third after chickpeas and lentils in production yield. Even though dry bean cultivation areas are decreasing, production is on the rise due to the development of new production techniques and introduction of high-yield varieties [1].

In the double logarithmic regression model used for the estimation of dry bean production, dry bean production decreased by 1.23% when there was a 1% increase in agricultural labor cost, and dry bean production decreased by 1.09% when there was a 1% increase in real diesel oil prices. There is a negative correlation between dry bean production and the real price of agricultural labor, real price of diesel oil, and the amount of rainfall; conversely, there is a positive correlation between dry bean production and real price of fertilizers and time [2]. The vast majority of dry bean farmers in Central Anatolia in Turkey (88%) uses cropping system (crop alternation). 65% of farmers apply it every two years. Farmers generally plant wheat, barley, corn, sugar beet, vetch, and potato after beans during the alternation period. Farmers who cultivate local populations generally prefer Dermason and AyseKadin beans [3].

Turkey is clearly a bean importer, and dry bean imports are projected to increase every year in the near future. As a result of the decrease in the production areas and the amount of production in the country, a decrease in dry beans export is also predicted [4].

There are studies in the literature where production yield modeling and forecasting of agricultural products has been done using artificial neural networks (ANN) and time series methods.

ARIMA and exponential smoothing methods have been used for banana production modeling [5] and forage crop production modeling and forecasting [6]. Box-Jenkins models have been used for potato [7] and peanut production models [8] and artificial neural networks have been used for orange [9], animal beet [10] and tobacco production [11] modeling and forecasting. Time series and artificial neural networks have been used for tangerine production modeling [12], and cotton production has been modeled using Holt, Brown and Damped methods [13]. The double exponential smoothing method has been applied for dried beans [4].

The aim of this study was to model and forecast dry bean production yield in Turkey using ANN and time series analysis.

II. MATERIAL AND METHOD

Material and Method

Material

The material of the research is 1970-2019 dry beans production amount values provided from the www.tuik.gov.tr web address of Turkish Statistical Institute [14]. The dependent variable was dry beans production figures whereas the independent variable was year series. These variables were selected in order to be able to make reasonable estimations with the models to be selected with ANN and time series analysis methods.

Method

Artificial neural networks (ANN)

Artificial neural networks (ANN) are powerful machine learning techniques with the functions of estimation and approximation based on the input. Interconnected artificial neural networks mostly come off neurons that can calculate values from inputs and comply to different situations [15, 16].

ANN has got such as input layer, a hidden layer and an output layer. Input layer, a hidden layer and an output layer, respectively for input data, data processing, and output data, constitute layers of Multilayer Perceptron network (MLP). Each layer is comprised of several knots or artificial neurons. All neurons, save for those located in a layer, are connected to one another [17].

MLP classifier makes use of the following algorithm for calculating the inputs receiving an individual knot [18].

$$net_j = \sum_i w_{ij}\, I_i$$

where net_j is the input parameter that receives the individual neuron j, W_{ij} shows the weights between neurons i and j, and I_i stands for the output of neuron i belonging to the sender, input or hidden layer. The output value resulting from neuron j is computed through following [18]:

$$O_j = f(net_j)$$

where the f function is usually a nonlinear sigmoid function. Namely, it is activation function. The utilized activation functions in configuration of ANNs in the case of this study were:

Hyperbolic tangent sigmoid transfer function (tansig):

$$f = \frac{2}{1 + e^{-net_j}} - 1$$

purlin function generates outputs in the range of -∞ to +∞, logsig function produces outputs in the range of 0 to 1, and tansig function produces outputs in the range of -1 to +1 [19].

To evaluate the precision of the predicted discharge volume, Mean Square Error (MSE) [20] and Mean Absolute Error (MAE) [21] were used:

$$MSE = \frac{\sum_{i=1}^{N}(\widehat{I_i} - I_i)^2}{N}$$

$$MAE = \frac{\sum_{i=1}^{N}\left|\widehat{I_i} - I_i\right|}{N}$$

where$\widehat{I_i}$ is the estimated discharge for sample i, I_i is the discharge volume obtained from reference data, and N is the number of samples.

Time Series Analysis

A pth-order **autoregressive model** AR(p) model is denoted as [22].

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t$$

An **AR(p) model** uses a linear combination of past values of the target to make forecasts.

A qth-order moving average process, expressed MA(q), is characterized by [23].

$$y_t = -\theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} + e_t$$

ARMA(p,q) model composed of apth-order **autoregressive and** qth-order moving average process and it is characterized by [24].

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

III. RESULTS AND DISCUSSIONS

The artificial neural networks and time series analysis method goodness of fit statistics (MAE and MSE) of dry beans production between the years 1970-2019 in Turkey are showed in Table 1.

Table 1. ANN and time series analysis models for production amount

Model	MSE	MAE
ANN	177 883 369	10 948
AR(1)	313 348 308	12 194
MA(1)	564 892 155	19 929
ARMA(1,1)	317 916 032	12 037
ARMA(1,2)	322 656 436	12 199
ARMA(2,1)	324 620 181	12 052

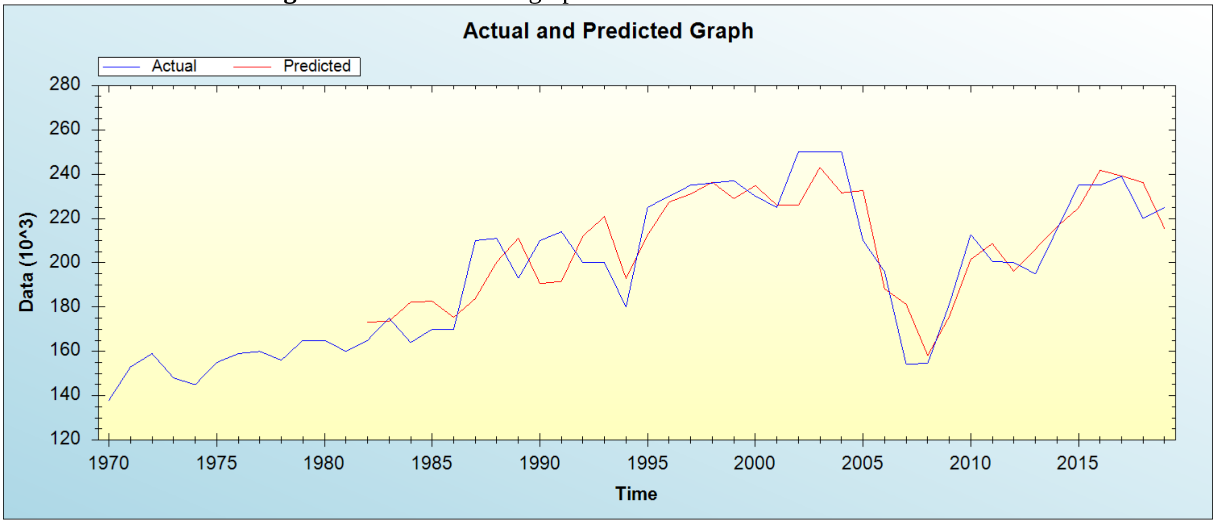
When Table 1 is examined, when the time series analysis and artificial neural network methods are compared according to mean square error (MSE) and Mean Absolute Error (MAE) values, artificial neural networks (ANN) with minimum MSE and MAE values are the most suitable model. The estimated and residual values are presented in Table 2 together with the real values of the ANN method.

Table 2. Observed, estimated and residual values

Years	Actual	Predicted	Residual
2005	210000	232579.867	-22579.867
2006	195970	188191.461	7778.539
2007	154243	181288.277	-27045.277
2008	154630	158145.106	-3515.106
2009	181205	175644.325	5560.675
2010	212758	201490.088	11267.912
2011	200673	208660.479	-7987.479
2012	200000	196138.576	3861.424
2013	195000	206186.654	-11186.654
2014	215000	216250.081	-1250.081
2015	235000	224703.267	10296.734
2016	235000	241680.767	-6680.767
2017	239000	239191.079	-191.079
2018	220000	236144.955	-16144.955
2019	225000	215373.905	9626.095

The graph of the observed and estimated values obtained with ANN method are displayed in Figure 1.

Figure 1. The combined graph of observed and estimated values



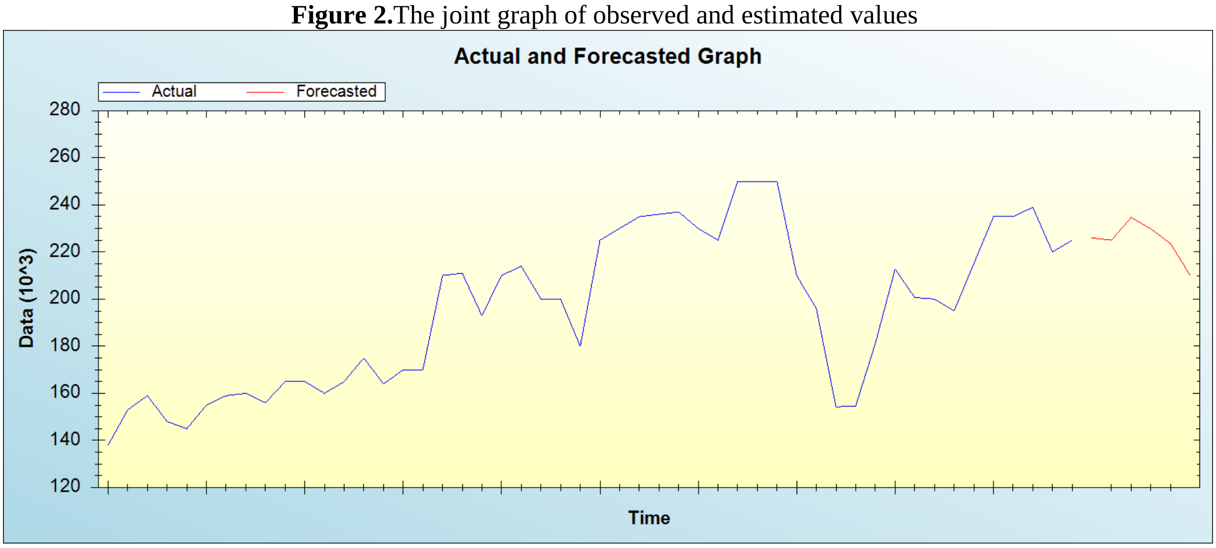
The possible 2020-2025 values of dry beans production forecasted with ANN are given in Table 3.

Table 3. Dry beans production amount estimation

Years	Forecasted
2020	225 955
2021	225 031
2022	234 660
2023	229 793
2024	223 506
2025	210 126

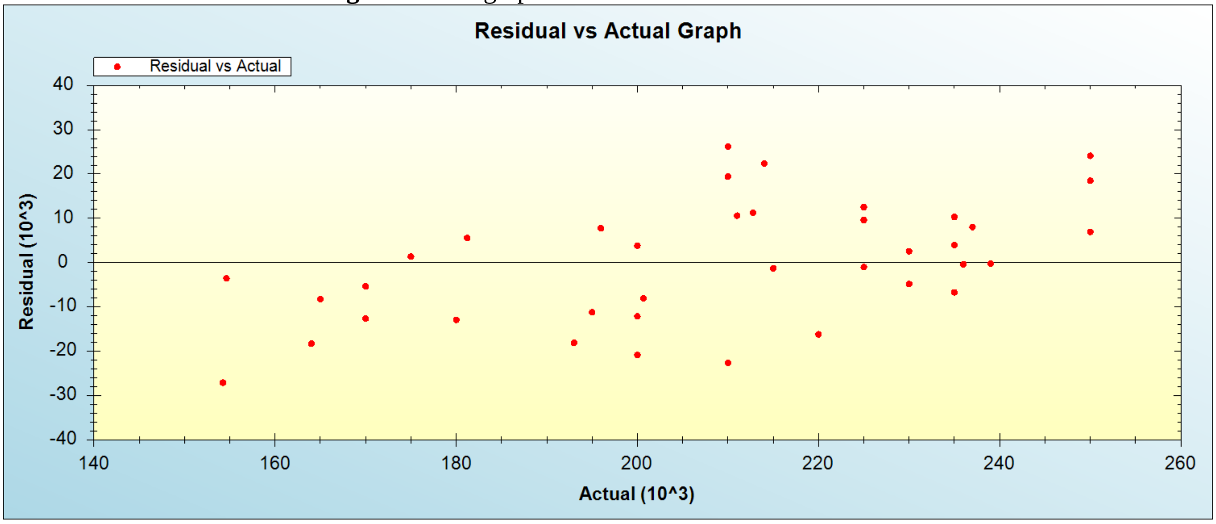
As shown in Table 3, while the dry bean production yield is approximately the same in 2020 and 2021, there will be a slight increase in 2022. It will start to decrease by 2023. The graph showing the observed and forecasted values of dry bean yield is given in Figure 2.

Figure 2. The joint graph of observed and estimated values



As seen in Figure 2, the forecast shows that dry bean yield, which has slightly decreased since 2019, will increase slightly in 2022 and may decrease again in the following years. In Figure 3, when the joint graph of observed and residual values was observed, residual and observed values were found to be scattered free from each other and randomly. This situation shows that important hypotheses regarding the model are ensured.

Figure 3. Joint graph of observed and residual values



[4] modeled and predicted dry bean yield with the double exponential smoothing method according to 1994-2014 data. They used MAPE, MAD and MSD statistics that are among the goodness of fit criteria. The authors reported a decrease in dry bean yield and cultivation area in recent years in Turkey.

Animal beet production modeling was carried out in another study using artificial neural networks for plant and animal production modeling. Artificial neural networks and trend analysis methods were compared, and artificial neural networks provided better forecasts [10]. Artificial neural networks and multiplicative decomposition methods have been studied on tobacco production. When compared with respect to MSE statistics, artificial neural networks gave better forecasts, as was the case in this study [11].

IV. CONCLUSION

Dry beans production amount in Turkey was estimated through artificial neural networks and time series analysis (AR, MA and ARMA) in the study. The years (1970-2019) were used as the input variable, as 1 independent variable and dry beans production values were used as the output variable. Then, the training, test and verification processes of the network were made and estimation was performed. The results obtained have revealed that the ANN model established has given better results than trend analysis methods. Low MSE and MAE statisticsin the training, test and verification phases also support the results.

When we look at dry bean yield forecasts, we can conclude that the yield, which was 225,000 tons in 2019, will decrease by 6.61% and be 210,126 tons in 2025. This is a significant production loss for this plant, which has an important place in nutrition, especially considering the increasing Turkish population. Measures should be taken in relevant national production plans to address this problem.

Compared to time analysis, artificial neural networks were generally more successful in predicting current data. It is thought that creating a production forecasting model using artificial neural networks and by comparing these to alternative techniques will provide better results for future predictions.

Conflict of interest

There is no conflict to disclose.

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