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Modelling and estimation of chickpea production in Turkey using Artificial Neural Networks and Time Series Analysis

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Abstract:*The aim of this study is to show that production design may be applied using artificial neural networks (ANN) and time series analysis in the establishment of chickpea 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 suitable of the model developed was determined using statistical parameters such as Square Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Bayesian Information Criterion (BIC).The results show that chickpea 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 chickpea production prediction in Turkey.
Keywords:*ANN, time series analysis, production, chickpea.*

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I. INTRODUCTION

Legumes are the protein source for more than two billion people around the world. 22% vegetable proteins and 7% carbohydrates in human nutrition, 38% proteins and 5% carbohydrates in animal nutrition are derived from edible legumes in the world. Legumes are the cereal product that comes after cereals under cultivation and production in field crops [1].

Chickpeas (*CicerarietinumL.*) is a leguminous plant used in human and animal nutrition and as green manure which has been cultivated for many years both in our country and in the world, especially in the Middle East, Far East, Mediterranean, South America and Central America countries [2,3].

As can be seen from Table 1, India ranks first in the world chickpea rankings. It is followed by Australia in the 2nd place and Turkey in the third place. India covers 66.13% of the world production of chickpeas and the percentage of the production made by the top 10 countries with the highest production is 94.25%.

Table 1. Countries with the highest chickpea production in the world

Order	Countries	Production amount (tonnes)	Rate within the world (%)
1	India	11 380 000	66.13
2	Australia	998 231	5.80
3	Turkey	630 000	3.66
4	Russian Federation	620 400	3.61
5	United States of America	577 970	3.36
6	Ethiopia	515 642	3.00
7	Myanmar	509 856	2.96
8	Mexico	351 796	2.04
9	Pakistan	323 364	1.88
10	Canada	311 300	1.81
	Top 10 countries total	16 218 559	94.25
	Total (World)	**17 207 840**	

There are studies available on the production model and prediction in agriculture using Artificial Neural Networks (ANN) and Time Series Methods.

The modellings of banana production [4] and forage plant production quantity and prediction were made by ARIMA and exponential smoothing methods [5]. Production volume of nuts with Box-Jenkins models [6], potato [7] and peanut production model [8], orange with artificial neural networks [9], fodder beet [10] and tobacco production [11] modeling and prediction were investigated. Tangerine production [12] using time series and artificial neural networks, and cotton production using Holt, Brown, and Damped methods [13] were modeled. Regarding chickpea production, [14-16] applied time series analysis.

The aim of this study is to achieve the modeling and further prediction for the amount of chickpea production in Turkey through the ANN and Time Series Analysis.

II. EXPERIMENTAL PROCEDURE

2.1 Material

The material of the research is 1950-2019 dry beans production amount values provided from the www.tuik.gov.tr web address of Turkish Statistical Institute [17]. 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 performed using ANN and time series analysis methods.

2.2 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 [18,19].
The process of data normalization by the minimum/maximum method operated is displayed in Eq. (1) [20].

$$x' = \frac{x - Min(x)}{Max(x) - Min(x)} + \left(newMax(x) - newMin(x)\right) + newMin(x)$$

here x' is the new value, x is the old value, and min(x) and max(x) are the minimum and maximum values of attribute x, respectively. All transformed sample outputs are in the domain of [-1,-1] prior to ANN training.
In order to train the ANN, production values parameter were utilized for training and testing. During the training process, the weights were adjusted to make the actual outputs close to the target (measured) output of the network, by the L-M algorithm in accordance with the root mean squared error (RMSE).

To evaluate the precision of the predicted discharge volume, Square Mean Square Error (RMSE) [21] and Mean Absolute Error (MAE) [22] were used:

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

$$MAE = \frac{\sum_{i=1}^{N}\left|\widehat{I_i} - I_i\right|}{N} \tag{3}$$

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 modelAR(p) model is denoted as [23].

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

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 [24].

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

ARMA(p,q) model composed of apth-order autoregressive and qth-order moving average process and it is characterized by [25].

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

Exponential Smoothing Models

Holt's Method: Holt's Linear Trend method is an extension of exponential smoothing to take into account a local linear trend [26]. The two equations associated with Double Exponential Smoothing as following [27].

$$Y'_t = \alpha Y_t + (1-\alpha)(Y'_{t-1} + b_{t-1}) \qquad 0 \le \alpha \le 1$$
$$b_t = \gamma(Y'_t - Y'_{t-1}) + (1-\gamma)b_{t-1} \qquad 0 \le \gamma \le 1$$
$$\hat{Y}_{t+m} = Y'_t - b_t m$$

The current value (Y_t) of the series itself is used to calculate its smoothed value is the replacement in double exponential smoothing. A value of α is chosen to smooth the series and adapt to changes in level. A value of γ is chosen to allow the trend estimate to react to changes in the rate of growth of the series.

Brown's linear trend model: It is a special case of the Holt linear trend model. In this model, the parameters are assumed that the level and trend are equal. In this method, estimates are performed using the equations below [28].

$$Y_t^{'} = \alpha Y_t + (1-\alpha)(Y_{t-1}^{'})$$
$$Y_t^{''} = \alpha Y_t^{'} + (1-\alpha)(Y_{t-1}^{''})$$
$$a_t = 2Y_t^{'} - Y_t^{''}$$
$$b_t = \alpha/1 - \alpha(Y_t^{'} - Y_t^{''})$$
$$\hat{Y}_{t+m} = a_t + b_t m$$

Damped trend model: It is a exponential smoothing model that has performed well in numerous empirical studies, and it was well established as an accurate forecasting method.
The new stated damped trend model is written as follow [29].

$$Y_t = l_{t-1} + A_t b_{t-1} + \varepsilon_t$$
$$l_t = l_{t-1} + A_t b_{t-1} + (1-\alpha)\varepsilon_t$$
$$b_t = A_t b_{t-1} + (1-\beta)\varepsilon_t$$

Here Y_t is the observed series, l_t is its level and b_t is the gradient of its linear trend.

III. RESULTS AND DISCUSSIONS

The artificial neural networks and time series analysis method goodness of fit statistics (MAE and MSE) of chickpeas production between the years 1950-2019 in Turkey are showed in Table 2.

Table 2. ANN and time series analysis models for chickpeas production amount

Model	RMSE	MAE	BIC
ANN	55371.3	33957.5	21.158
ARIMA(1,1,0)	55952.4	35690.8	21.987
ARIMA(0,1,1)	55987.7	35707.2	21.989
ARIMA(1,1,1)	56256.8	35244.1	22.059
ARIMA(1,1,2)	56395.1	34594.0	22.126
ARMA(2,1,1)	56499.0	34772.5	22.129
Holt linear trend	55831.6	35358.3	21.982
Brown linear trend	59227.7	37401.8	22.039
Damped trend	56202.3	34000.9	22.056

Autocorrelations (ACF) and partial autocorrelation graphs (PACF) applied in time series are shown in Figure 1. When Figure 1 is examined, it is seen that many relation values in the ACF diagram of the series surpass the confidence limit. In other words, there is a trend but not stable. Therefore the first difference of the series is considered. ACF - and PACF diagrams of the series with the first difference are shown (Figure 2). In Figure 2 all relationship values are within the confidence limits. Quality of fit statistics such as RMSE, MAE, and BIC were examined to determine the model grade and the suitable method of the series. It was compared with the ANN model (Table 2).

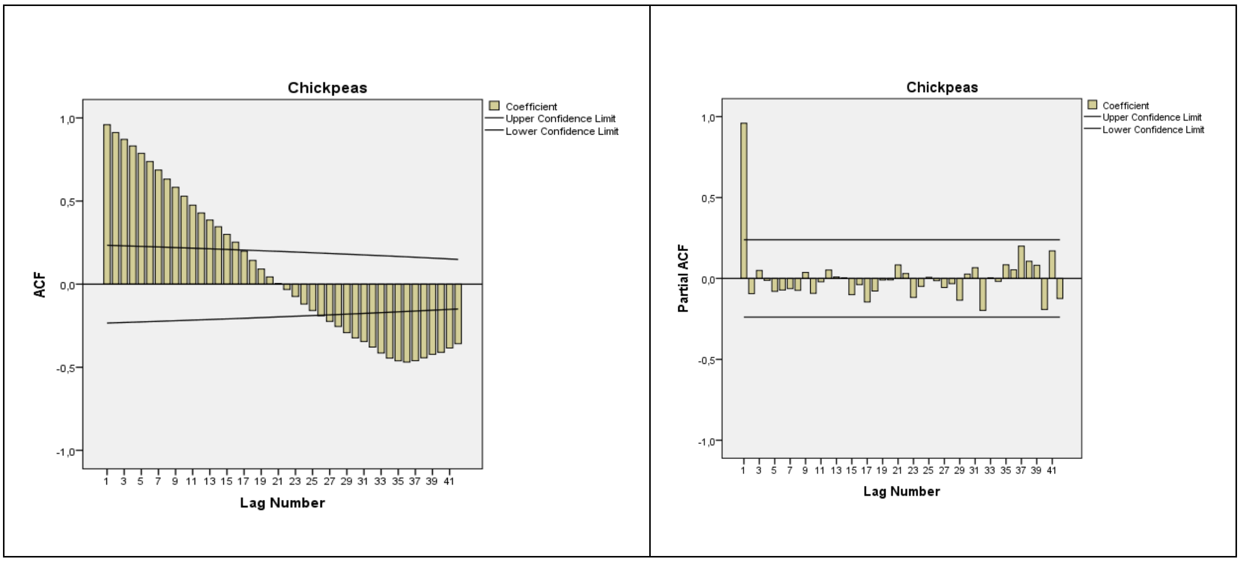

Figure 1. ACF and PACF graph for level series

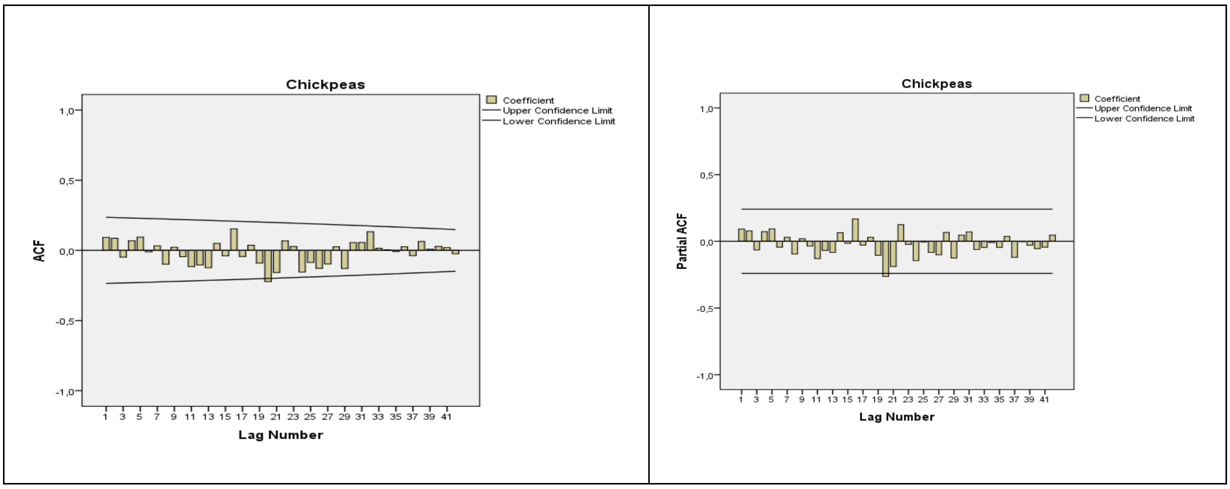

Figure 2. ACF and PACF graph for first difference

When Table 1 is examined, when the time series analysis and artificial neural network methods are compared according to square mean square error (RMSE) and Mean Absolute Error (MAE) values, artificial neural networks (ANN) with minimum RMSE and MAE values are the most suitable model. The hyperbolic tangent function was used as activation function when creating a model with the ANN method. The number of neurons in the input layer, the hidden layer and the output layer was determined as 1-12-1 each. 1000 iterations were used for the ANN method in the data series consisting of 70 observations between 1950-2019. The estimated and residual values are presented in Table 3 together with the real values of the ANN method.

Table 3. Observed, estimated and residual values

Years	Actual	Predicted	Residual
2000	548000	590604	-42604
2001	535000	579476	-44476
2002	650000	567025	82975,1
2003	600000	662992	-62992
2004	620000	625153	-5153,1
2005	600000	640983	-40983
2006	551746	625153	-73407
2007	505366	582988	-77622

2008	518026	537130	-19104
2009	562564	550155	12409,5
2010	530634	592935	-62301
2011	487477	562751	-75274
2012	518000	518106	-106,25
2013	506000	550128	-44128
2014	450000	537791	-87791
2015	460000	476103	-16103
2016	455000	487573	-32573
2017	470000	481860	-11860
2018	630000	498859	131141
2019	630000	648547	-18547

The graph of the observed and estimated values obtained with ANN method is showed in Figure 3.

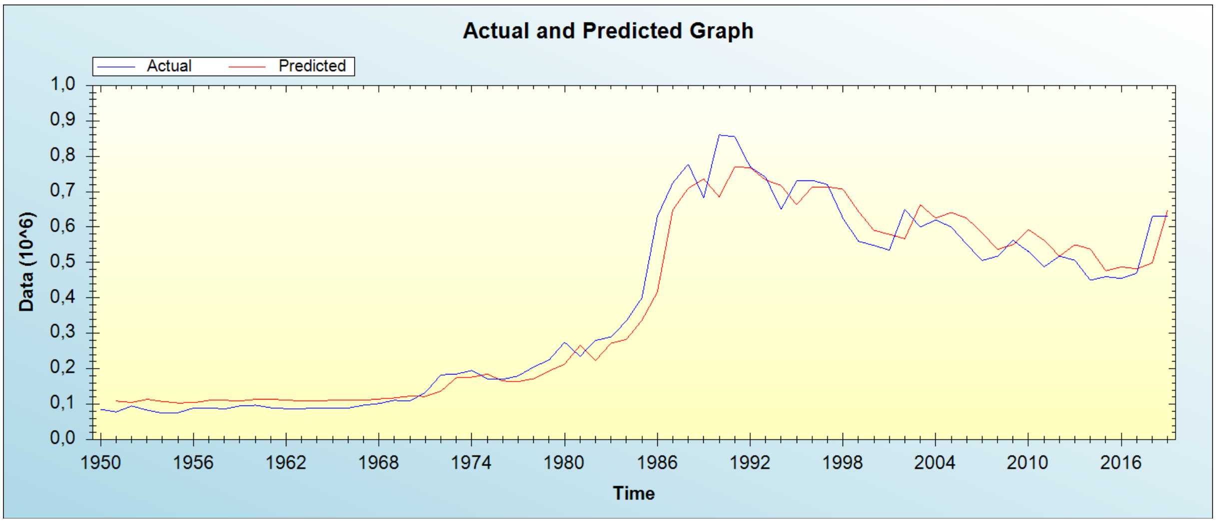

Figure 3. The combined graph of observed and estimated values for chickpea production

The possible 2020-2025 values of chickpea production forecasted with ANN are given in Table 4.

Table 4. Chickpea production amount estimation

Years	Forecasted
2020	648 547
2021	661 972
2022	671 215
2023	677 352
2024	681 329
2025	683 864

Table 4 shows that chickpea production will increase between 2020-2025. The graph showing the observed and predicted values of the chickpea production volume is shown in Figure 4.

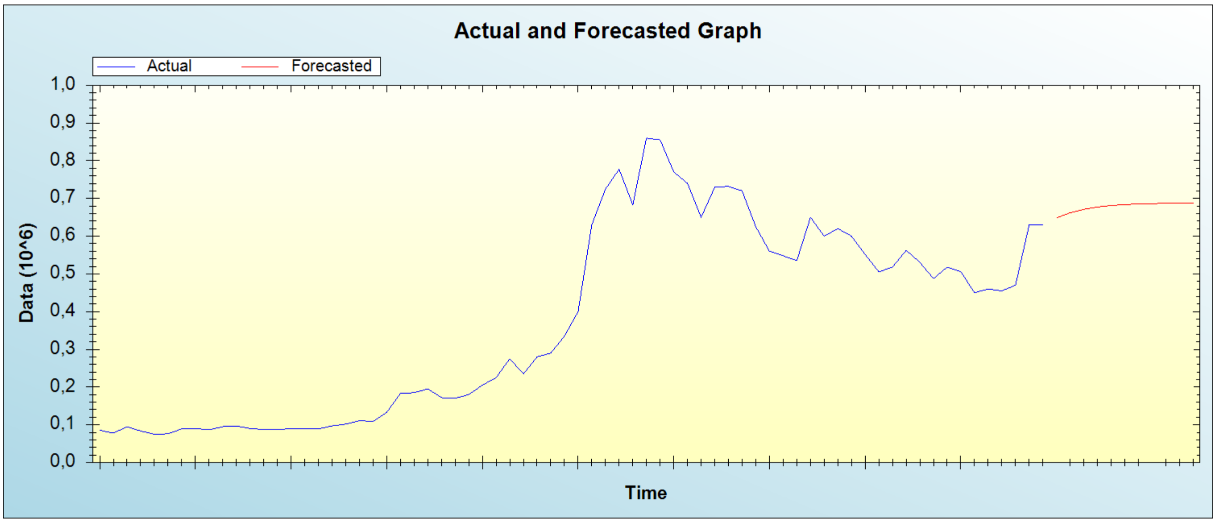

Figure 4. The joint graph of observed and estimated values

As can be seen in Figure 4, chickpea production will increase after 2019 and this increase will continue until 2025. In Figure 5, 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.

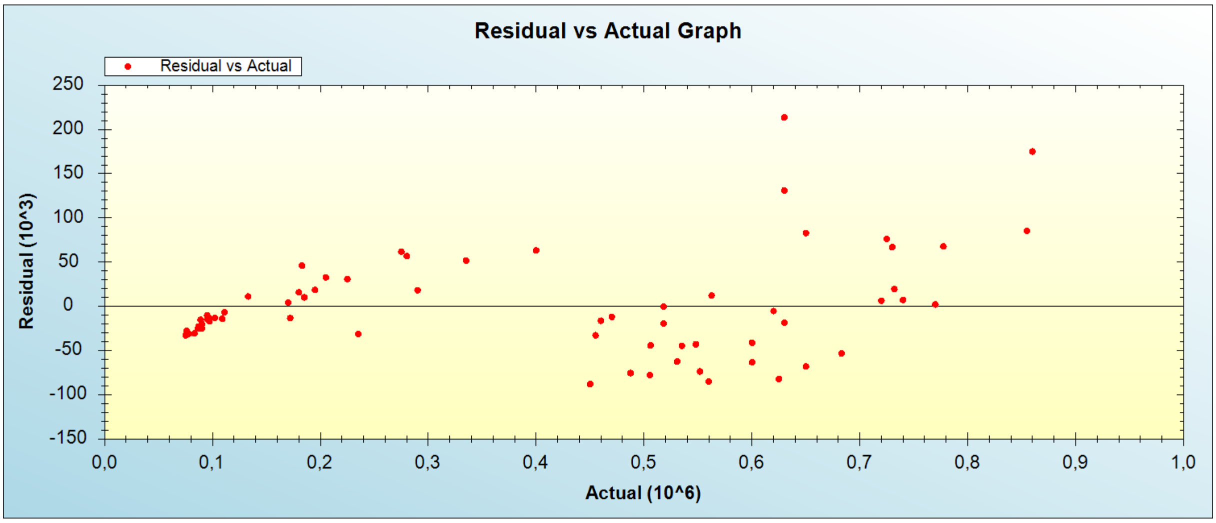

Figure 5. Joint graph of observed and residual values

In a study where chickpea production was modelled as ARIMA (1,3,1) in Turkey in the period 1985-2018, it was found that the series was stable as of the 3rd degree and it was presented that ARIMA modeled predictions for the production between 2019-2023 (1,3,1) would be in the range of 768 406 -1 780 729 [16]. The result obtained in this study was found to be different from the ARIMA model. [14] found the chickpea production series in Bangladesh to be stable at the 1st degree and determined the ARIMA model (0,1,0). They used MAE, MSE, RMSE, AIC, BIC, MAPE, R^2 and $\bar{R}^2$statistics from the goodness of fit criteria. In another study, time series modeling of chickpea production amount in India from 1950-51 to 2007-08 was carried out and ARIMA (1,2,1) model was obtained. The chickpea production amount was projected between 2008-09 and 2019-20 [30].

IV. CONCLUSION

Chickpea production amount in Turkey was estimated through artificial neural networks and time series analysis (AR, MA, ARMA, Holt linear, Brown linear and Damped trend) in the study. The years (1950-2019) were used as the input variable, as 1 independent variable and chickpea production values were used as the output variable. Then, the training, test and verification processes of the network were made and estimation was applied. The results obtained have set out that the ANN model established has given better results than trend

analysis methods. Low RMSE and MAE statistics in the training, test and verification phases also ground the results.
Considering the estimates of chickpea production, it has been noted that the production of 630 000 tons in 2019 will increase by 8.55% and reach 683 864 tons in 2025. This situation is an important result for chickpeas having an important place in the nutrition of human beings when the population growth is considered. It will be useful to encourage farmers to produce chickpeas in the country's production planning. In general, it has been observed that artificial neural networks are more successful in predicting available data compared to time analysis. In prediction studies, artificial neural networks can be used as an alternative method to the prediction model.

Conflict of interest
There is no conflict to disclose.

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