*J. Agric. Sci. Technol. (2024) Vol. 26(1): 1-11*

# Forecasting Sugar Beet Production in Turkey Using the Box-Jenkins Method

D. Sarica[1]

## ABSTRACT

**Turkey is a favourable country for sugar beet production due to its climate and soil composition, and it holds a significant position among the countries producing sugar beet. Therefore, in this study, an Autoregressive Integrated Moving Average (ARIMA) was used to project the sugar beet production values for Turkey over the next ten years. The most effective model structure [ARIMA (2, 1, 3)] was created for this purpose using data from 1925 to 2020. The years 2019 and 2020 were utilized as the model's validation years. When the observed and expected sugar beet production values are compared, the data indicates that the predicted values are slightly lower than the actual ones. The results also show that by 2030, sugar beet production in Turkey would reach 20.5 million tons. This research may help policymakers plan for the storage, export, or import of sugar beets. Also, by using these data, resource waste can be avoided.**

**Keywords:** ARIMA, Autoregressive integrated moving average, *Beta vulgaris* L., Output prediction.

## INTRODUCTION

The Turkish economy greatly benefits from the agriculture sector. Agriculture produces goods that are both final goods and sources of raw materials for the industrial sector. In this framework, one of the most significant industries is sugar beet farming. Due to its contribution to agricultural production, by-products, and employment, it not only serves as the primary component of nourishment but also plays a crucial strategic role in agriculture-based industrial production (Esturk, 2018).

Until the end of the 18th century, sugar was only produced from sugar cane, but in the 19th century, sugar beet farming and production in Europe began as a new raw material (Senturk, 2020). In 2021, 20% of the global sugar production was obtained from sugar beet and 80% from sugarcane (TEPGE, 2021). Geographically, some countries, such as Turkey, the European Union (EU), Russia, and Ukraine, produce sugar from beets; others, such as the United States of America (USA), Japan, and China, produce sugar from both beets and canes; and yet others, such as Brazil, Mexico, Pakistan, Thailand, India, and Australia, produce sugar from canes (TURKSEKER, 2020).

According to the Food and Agriculture Organization of the United Nations (FAO, 2022), in 2020, world sugar beet production was nearly 252.9 million tons, reaching the lowest value in the last five years. Production of sugar beets decreased in this period by 10%. The main reason for this drop was a more than one million ton decline in the EU's production in Western Europe over the prior period (TURKSEKER, 2020). Furthermore, the most important producers of sugar beet were Russia (33.9 million tons), the United States of America (USA) (30.5 million tons), Germany (28.6 million tons), France (26.2 million tons), and Turkey (23 million tons) in 2020. Also, the top three importing countries of sugar beet in 2020 were Switzerland (277.3 thousand

[1] Department of Agricultural Economics, Faculty of Agriculture, Isparta University of Applied Sciences, 32260, Isparta, Türkiye.
Corresponding author; e-mail: denizsarica@isparta.edu.tr



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

tons), China (178.1 thousand tons), and Czechia (176.8 thousand tons), while the top three exporting countries were Germany (349.8 thousand tons), Slovakia (160.6 thousand tons), and Belgium (142 thousand tons), respectively (FAO, 2022). Regarding world sugar consumption, India ranks first with 26.1 million tons, followed by the EU with 16.5 million tons. Turkey is in twelfth place in the world in terms of consumption, with 2.7 million tons (TURKSEKER, 2020).

As seen from the production data, Turkey is a suitable region for sugar beet cultivation due to its climate and soil types, and it has an important position among the countries producing sugar from beet. All of the sugar produced in Turkey is obtained from sugar beet, which contains 25% more sugar than sugarcane (Kaya, 2021). Sugar beet, which is one of the main products in Turkey's agricultural production, is also important in terms of its contribution to the agricultural industry and its by-products and contributions to animal husbandry. Sugar has a strategic value as a staple food, and Turkey's annual sugar needs are planned to be met proportionally with 90% beet sugar and 10% starch-based sugar (Unsal, 2022). Proper forecasting of such significant commercial crops is critical in an economic system. Crop production and crop prices are inextricably linked. An unforeseen drop reduces farmers' marketable surplus and income, causing prices to rise. A surplus of production can cause a drop in prices and harm farmers' incomes. The effect of the price of a vital product has an important impact on the incomes, wages, inflation rate, and several policies in an economy. In the case of commercial crops such as sugar beet, production level influences raw material costs and market competitiveness (Suresh and Priya, 2011). Moreover, an accurate and timely forecast of sugar beet yearly production will greatly aid the sugar beet industry's decision-making in terms of cash flow, value chain, and other factors. As a result, the more accurate the model is estimated, the greater the significance and application of the research. Therefore, sugar beet production in Turkey is aimed at being forecast using an Autoregressive Integrated Moving Average (ARIMA) model in this research.

There is a substantial body of literature on employing ARIMA models to forecast sugarcane productivity. Other crops, such as cotton (Debnath *et al*., 2013; Kumar *et al*., 2017), maize (Badmus and Ariyo, 2011; Ramesh *et al*., 2014; Sharma *et al*., 2018), wheat (Iqbal *et al*., 2005; Biswas *et al*., 2014; Nath *et al*., 2019), rice (Khan *et al.*, 2015; Tinni Chaudhuri *et al*., 2020), and potato (Hossain and Abdulla, 2016; Celik, 2019) are also being studied. However, no comprehensive research on sugar beet production forecasting has been conducted, and only one study (Sahinli, 2021) analysing sugar beet prices for Turkey forecasting using ARIMA could be found. Here are a few noteworthy scientific studies focusing on the specific products:

Vishwajith *et al*. (2016) sought to estimate the area, productivity, and sugar production of India as well as the main sugarcane-developing provinces of India, by fitting univariate ARIMA models. For the study, the authors examined time series data on sugarcane production, area, productivity, and sugar production that were gathered from 1950 to 2012. They demonstrated that both sugar and sugarcane production will expand in area, production, and yield in India and India's key sugarcane-producing states.

Similarly, Harlianingtyas *et al*. (2020) aimed to forecast the amount of sugarcane produced at the Asembagus Sugar Mill over five years. They adopted the Box-Jenkins ARIMA method for this purpose, making comparisons in the measurement of predicting outcomes with the trend and exponential smoothing methods. They used the data from 1979 to 2018, derived from secondary data from the Asembagus factory registry outputs. The findings of the forecast indicated that sugarcane production was rising annually.

Mishra *et al*. (2021) attempted to establish suitable forecasting models for sugarcane production employing the ARIMA technique. India was chosen, along with the top



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

sugarcane-producing states of Andhra Pradesh, Tamil Nadu, Maharashtra, Karnataka, and Uttar Pradesh. Data on sugarcane production was used from 1950 to 2015. They determined that sugarcane production would rise in the following years, reaching a total of 40.6468 million tons in India in 2025. Furthermore, between 2019 and 2025, sugarcane production in Tamil Nadu and Andhra Pradesh declines while it increases in Uttar Pradesh, Maharashtra, and Karnataka.

Paswan *et al*. (2022) investigated the long-term viability and stability of sugarcane production in Bihar, India. The Box-Jenkins ARIMA model and an artificial neural network approach were employed to forecast sugarcane production. The results showed an important increase from 126.03 million tons in 2020 to 131.67 million tons in 2025.

This study's main goal is to provide background information to aid in the development of national food policies. It is also intended to shed light on the researchers and farmers who make critical decisions regarding sugar beet production. Therefore, the primary objective of the research is to identify the best model and forecast Turkish sugar beet production for the next 10 years. The time series data from 1925 to 2020 is employed for sugar beet production. To achieve the study's ultimate purpose, data will be analyzed using the ARIMA model. As far as we know, no such procedure has been reported to be used in forecasting Turkish sugar beet production. This study differs significantly from previous studies in the area of sugar beet production. Furthermore, the study may help design future large-scale research.

## MATERIALS AND METHOD

### Data

The data on sugar beet production (tons) was collected for a duration of 96 years, from 1925 to 2020, by the Turkish Statistical Institute (from 1925 to 1960) (TSI, 2012) and FAO (2022) (from 1961 to 2020). The data from 1925 to 2018 was employed to develop the most appropriate model structure. In order to validate the model, the last two years (2019–2020) were used.

Descriptive statistics are helpful to identify patterns and overarching trends in data. The statistics present the data set in a suitable and comprehensible manner using numerical and graphical tools. The series was explained using some significant statistical variables, including mean, standard error, minimum, maximum, etc. (see Table 1).

The annual minimum value of the sugar beet production in Turkey is 6.5 thousand metric tons while the maximum is 23 million metric tons during the research period. The overall average sugar beet production for nearly 100 years has been 7.8 million metric tons. The median represents the value located in the middle of an ordered list of values. This value is lower than the mean and is 5.8 million metric tons. The median, unlike the mean, is unaffected by outlier values. Regarding the Jarque-Bera test, it is based on the traditional skewness and kurtosis measures. It is a "goodness of fit" test that determines whether the sample data has skewness and kurtosis that match the normal distribution. The Jarque-Bera value is 8.707, so, the null hypothesis that residuals are normally distributed cannot be rejected. Normality is not an essential assumption for a linear regression like ARIMA (Lumley *et al*., 2002). Therefore, this result does not pose a problem for the continuation of the analysis.

**Table 1.** Descriptive statistics of sugar beet production in Turkey.

| Summary of statistics | |
|---|---|
| Mean | 7,808,259 |
| Median | 5,801,595 |
| Maximum | 23,025,738 |
| Minimum | 6,484 |
| Skewness | 0.393 |
| Kurtosis | 1.752 |
| Jarque-Bera | 8.707 |

**Note**: The statistics were performed in EViews 10.



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

## Estimation Method

The methods used in time series analysis are separated into two groups: multivariate and univariate time series estimation methods. The Box and Jenkins (1970) estimation method is one of the techniques used in univariate time series that makes forward-looking estimations with statistical methods. In the study, this estimation method was employed to forecast sugar beet production in Turkey. The time series must have discrete, stationary, and evenly spaced observation values to apply the method (Akdag and Yigit, 2016). The three most common linear stationary Box-Jenkins models are Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA), which combines AR and MA models (Ataseven, 2013). The Box-Jenkins method's ability to employ previous observation values as an explanatory variable is a key benefit. Box-Jenkins estimation techniques are an experimental process rather than a method expressed with a model that can be predetermined. They can choose the best model from a variety of options and track the suitability of the chosen model for the examination at each stage.

A typical notation for an ARMA model is ARMA (p, q), where p and q stand for the orders of autoregression and moving average, respectively. The time series is a linear function of actual past values and random shocks in the ARMA model (Kiran, 2014). A stationary time series, ARMA (p, q), is defined as in Equation (1):

$$Y_t = \delta + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \cdots + \theta_P Y_{t-p} + \varepsilon_1 + \varphi_1 \varepsilon_{t-1} + \cdots + \varphi_q \varepsilon_{t-q} \quad (1)$$

Where, $\delta$ is a constant about the mean of Y. $Y_t$ is the dependent variable at time t and $Y_{t-1}$, $Y_{t-2}$,…,$Y_{t-p}$ are the independent variables at lags t-1, t-2,…, t-p, respectively. $\theta$s are the coefficients to be estimated. $\varepsilon$s are the error terms that are an uncorrelated random variable with zero mean and a constant variance. $\varphi$s are also coefficients to be estimated.

The ARMA (p, q) process combines the AR (p) and MA (q) elements as well as the stability and convertibility conditions. When the ARMA process is stationary, it will have a fixed mean. For example, the stationarity of the ARMA (1, 1) process depends on the autoregressive part of the process, and its reversibility depends on the moving average part of the process. If $\theta < 1$, the process will be stationary, and if $\varphi < 1$, the process will be reversible.

AR, MA, and ARMA processes are methods applied to stationary series. A non-stationary process needs to be made stationary. Therefore, a non-stationary time series can be made stationary by taking the difference to the appropriate degree. In this case, the original series is called a homogeneous non-stationary series. The time series, which are not stationary but made stationary by taking the difference, comply with the autoregressive integrated moving average [ARIMA (p, d, q)] processes. Here, d stands for integration (differencing). To apply the Box-Jenkins method to the forecasting of non-stationary time series, the series must first be made stationary. To verify stationarity, a visual inspection of the data graph, the autocorrelation's structure, and partial correlation coefficients are helpful. Application of the unit root test is another method of determining stationarity. If it turns out that the model is non-stationary, differencing the series will bring it into stationarity. The Generalized Least Square Dickey-Fuller (DF-GLS) (Elliott *et al*., 1996) unit root test was employed in the study to achieve this goal. Furthermore, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graphs were drawn, and it was tried to visually determine (via a correlogram) what kind of development the series included.

The identification process moves on to find the initial values for the orders of parameters, p and q, after evaluating whether the series is stationary. One or more



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

models that appear to offer statistically appropriate representations of the relevant data are tentatively selected during the identification stage. The model's parameters are then precisely estimated using least squares.

Both individually and collectively, several models are run for various AR and MA combinations. Low Akaike (AIC) or Schwarz (SIC) information criteria, the absence of autocorrelations for residuals, and the significance of the parameters are used to determine which model is the best. The information criteria put forward by Akaike (1974) and Schwarz (1978) are two of the criteria used to choose among time series models. The values of the SIC and the AIC must be small. The delayed order, in which values are small, is acknowledged as the proper delay order. Therefore, the model with the smallest information criterion value is selected.

Furthermore, the Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE) calculations are the extensively used error criteria to check the model's accuracy. In the study, the MAPE is used as an error measurement, and Equation (2) shows the calculation of the MAPE (Akgul, 2003).

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \qquad (2)$$

Where, n is the number of observations, $x_t$ is the t$^{th}$ independent variable, and $\hat{x}_t$ is the prediction of the tth independent variable.

## RESULTS AND DISCUSSION

As mentioned earlier, forecasting the Turkish sugar beet production until 2030 was done by employing trend analysis via the ARIMA Box-Jenkins approach in this study. Figure 1 depicts the outcome of a time-series plot of sugar beet production from 1925 to 2020, and there was an upward trend in sugar beet production in this specified period.

To obtain robust results from the model analysis, we first performed a unit root test. Thus, the DF-GLS unit root test was used, and the results are shown in Table 1. Elliott *et al*. (1996) improved the ADF test and proposed an efficient method for determining if a single time series had a unit root. In terms of small sample size and power, the DF-GLS test outperforms the augmented Dickey-Fuller (ADF) test. Furthermore, Ng and Perron's (2001) Modified Akaike Information Criterion

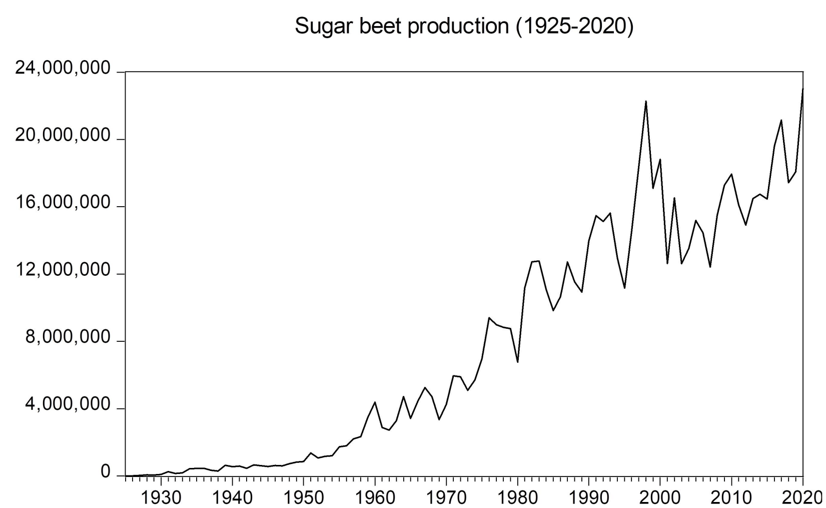


**Figure 1.** Time series plot for sugar beet production from 1925 to 2020 in Turkey. Note: The graph was performed in EViews 10. (Source: Author's calculations).



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

(MAIC) establishes the optimal lag order, and the Schwert Criteria determine the maximum lag length (Schwert, 1989). In the DF-GLS test, the H0 hypothesis is as follows: There is a unit root in the series. The data series was tested under the linear trend and constant cases, and the series was non-stationary in the constant case although it was stationary in the linear trend case. The first-order differencing technique was used to make it stationary, and the results are shown in Table 2.

As a result, there is no need to differentiate the time series further, and we obtain d= 1 for the ARIMA (p, d, q) model. This test allows us to progress in the ARIMA model development process by defining appropriate values for p in AR and q in MA in the model. Therefore, the next step is to inspect the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graphs and statistics for the stationary and non-stationary time series, as discussed in the material and methods section (see Figure 2).

The ACF and PACF graphs were investigated in the detection of the ARIMA model for the sugar beet production series. There is no autocorrelation or partial autocorrelation in the series since it was determined that the lag values were within the limits and the coefficients were not related to each other.

Many different ARIMA models were investigated, and the ARIMA (2, 1, 3) model, which gave the best statistical results, was obtained. The results of the model are given in Table 3. According to the results, all variables were found to be statistically significant.

Furthermore, the DF-GLS unit root test was applied by creating the residual variable of the model to determine the accuracy of the model, and the hypothesis of "H0= There is a unit root" was rejected (see Table 4).

When the ACF and PACF graphs of the residual values of the ARIMA (2, 1, 3) model were examined, it was seen that there was no fluctuation, the limits of significance were not exceeded, and the model had appropriate levels for forecasting (see Figure 3). Based on these evaluations, it is clear that ARIMA (2, 1, 3) is the best model for the sugar beet series.

Table 3 demonstrates the MAPE of the model in the last row. The lower the value, the better the model will be because the value represents the goodness of the model (Chen *et al*., 2008). The MAPE is 15.20, and this finding shows that the MAPE is compatible with the R-squared, which represents the goodness of fit of the model.

Using sugar beet production data from 1925 to 2018, the ARIMA model was used to forecast for the period 2018–2030. Figure 4 depicts the actual and forecast graphs for sugar beet production for the aforementioned period. When the observed and predicted sugar beet production values are compared, the data shows that the predicted values are slightly lower than the

**Table 2.** DF-GLS time series unit root test. [a]

| | Lag | Constant | Critical values | Lag | Linear trend | Critical values |
|---|---|---|---|---|---|---|
| I(0) | 3 | 1.593 | (1%) -2.590<br>(5%) -1.944<br>(10%) -1.614 | 0 | -3.634 | (1%) -3.599<br>(5%) -3.046<br>(10%) -2.755 |
| I(1) | 2 | -8.924 | (1%) -2.590<br>(5%) -1.944<br>(10%) -1.614 | 0 | -10.681 | (1%) -3. 603<br>(5%) -3.049<br>(10%) -2.758 |

[a] Note: The test was performed in EViews 10. (Source: Author's calculations)



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

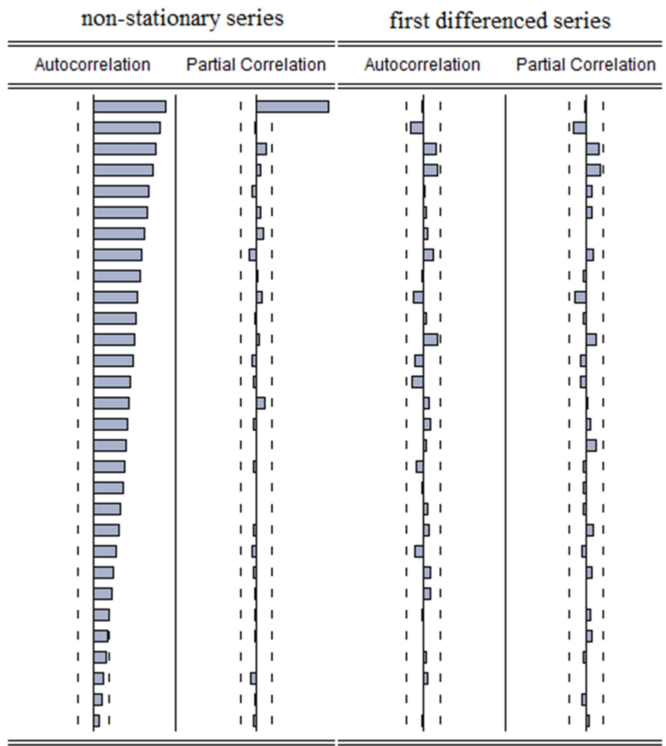


**Figure 2.** ACF and PACF graphs of non-stationary and first differenced series. Note: The correlogram was performed in EViews 10. (Source: Author's calculations).

**Table 3.** Results for the ARIMA (2, 1, 3) model of the sugar beet production series. [a]

| TYPE | Coefficient | Std. error | P-value |
|---|---|---|---|
| C | 159059.3 | 69546.52 | 0.0053 |
| AR(1) | -0.142416 | 0.079405 | 0.0764 |
| AR(2) | -0.743550 | 0.076500 | 0.0000 |
| MA(1) | -0.228103 | 0.084537 | 0.0084 |
| MA(2) | 0.586040 | 0.071255 | 0.0000 |
| MA(3) | -0.646350 | 0.069726 | 0.0000 |
| R-squared | 0.255337 | | |
| F-statistics | 4914741 | | |
| AIC | 31.43664 | | |
| SIC | 31.62727 | | |
| HQ | 31.51361 | | |
| Durbin-Watson stat. | 1.862120 | | |
| MAPE | 15.20008 | | |

**Note:** The model was performed in EViews 10. (Source: Author's calculations).

**Table 4.** DF-GLS time series unit root test for residuals.

| | Lag | Constant | Critical values | Lag | Linear trend | Critical values |
|---|---|---|---|---|---|---|
| I(0) | 0 | -7.941 | (1%) -2.590<br>(5%) -1.944<br>(10%) -1.614 | 0 | -8.597 | (1%) -3.610<br>(5%) -3.056<br>(10%) -2.764 |

Note: The test was performed in EViews 10. (Source: Author's calculations).



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.109 | 0.109 | 1.1361 | 0.286 |
| | | 2 | -0.001 | -0.013 | 1.1363 | 0.567 |
| | | 3 | 0.205 | 0.210 | 5.2805 | 0.152 |
| | | 4 | 0.264 | 0.230 | 12.177 | 0.016 |
| | | 5 | 0.173 | 0.153 | 15.190 | 0.010 |
| | | 6 | -0.039 | -0.097 | 15.346 | 0.018 |
| | | 7 | 0.192 | 0.130 | 19.146 | 0.008 |
| | | 8 | 0.156 | 0.018 | 21.681 | 0.006 |
| | | 9 | 0.012 | -0.040 | 21.696 | 0.010 |
| | | 10 | 0.063 | 0.023 | 22.121 | 0.014 |
| | | 11 | 0.257 | 0.206 | 29.231 | 0.002 |
| | | 12 | 0.214 | 0.133 | 34.228 | 0.001 |
| | | 13 | -0.159 | -0.208 | 37.030 | 0.000 |
| | | 14 | 0.018 | -0.063 | 37.065 | 0.001 |
| | | 15 | 0.065 | -0.150 | 37.550 | 0.001 |
| | | 16 | 0.138 | 0.098 | 39.730 | 0.001 |
| | | 17 | 0.030 | 0.097 | 39.836 | 0.001 |
| | | 18 | -0.128 | -0.101 | 41.761 | 0.001 |
| | | 19 | 0.042 | -0.083 | 41.971 | 0.002 |
| | | 20 | 0.033 | 0.001 | 42.101 | 0.003 |
| | | 21 | -0.038 | -0.053 | 42.282 | 0.004 |
| | | 22 | -0.090 | -0.125 | 43.291 | 0.004 |
| | | 23 | -0.048 | -0.085 | 43.587 | 0.006 |
| | | 24 | -0.109 | -0.106 | 45.114 | 0.006 |
| | | 25 | -0.193 | -0.067 | 49.955 | 0.002 |
| | | 26 | -0.050 | 0.033 | 50.279 | 0.003 |
| | | 27 | -0.088 | -0.089 | 51.315 | 0.003 |
| | | 28 | -0.073 | -0.063 | 52.045 | 0.004 |
| | | 29 | -0.127 | 0.057 | 54.287 | 0.003 |
| | | 30 | -0.172 | -0.042 | 58.437 | 0.001 |

**Figure 3.** ACF and PACF graphs of the residual values of the ARIMA (2, 1, 3) model. Note: The correlogram was performed in EViews 10. (Source: Author’s calculations).

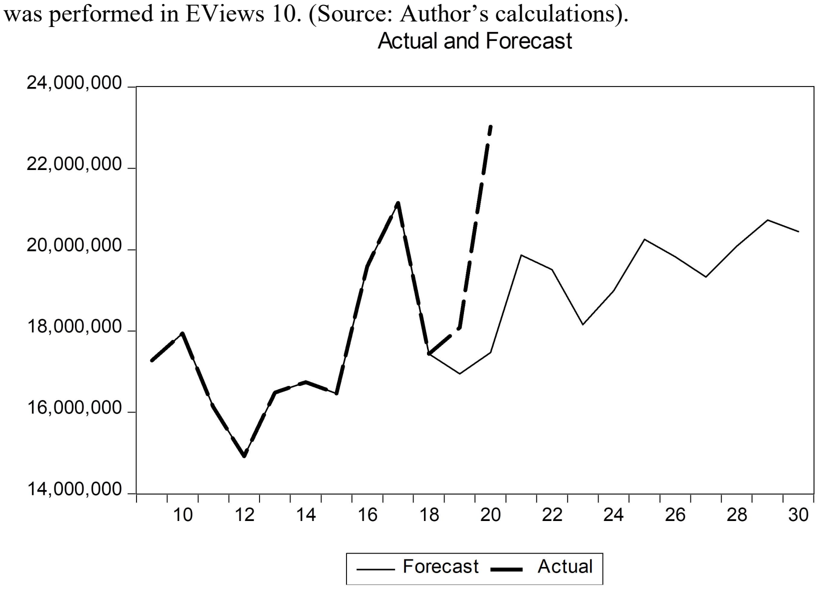


**Figure 4.** Actual (1925-2020) and forecasted (2018-2030) data graphs for sugar beet production. Note: The graph was performed in EViews 10. (Source: Author’s calculations).



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

**Table 5.** Performance of the model ARIMA (2, 1, 3).

| Year | Observed production | Predicted production | % Of deviation (±) |
|---|---|---|---|
| 2019 | 18,085,528 | 16,948,696 | -6.29 |
| 2020 | 23,025,738 | 17,473,245 | -24.11 |

Note: The graph was performed in EViews 10. (Source: Author's calculations).

actual values. Figure 4 reveals that the predicted values for sugar beet production are very close to the observed values. For example, in 2019, the observed production was 18.1 million tons, while the predicted one was 16.9 million tons. Hence, the deviation percentage in the model is 6.29 (see Table 5).

Furthermore, the sugar beet production forecast from 2019 to 2030 has gradually increased and will have reached 20.5 million tons by 2030. This can be a guide for policymakers as they prepare to determine policies based on future sugar beet production. These forecast values can be used to formulate food policies, particularly for sugar production.

## CONCLUSIONS

Due to its climate and soil type, Turkey is a suitable region for sugar beet cultivation, and it holds an important position among countries producing sugar from beet. Forecasting such significant commercial crops correctly is critical in an economic system. In this study, the sugar beet production values in Turkey were estimated for the next ten years, using an ARIMA Box-Jenkins model. The data from 1925 to 2020 was used to develop the best model structure for this purpose. The last two years (2019-2020) were used to validate the model. When the observed and predicted values for sugar beet production were compared, the data showed that the predicted values were slightly lower than the actual values. Furthermore, the findings indicated that sugar beet production will have gradually increased and surpassed 20.5 million metric tons by 2030.

This type of application may allow policymakers to plan ahead of time for the storage, export, or import of sugar beets. Also, taking these precautions may prevent resource waste. As far as we know, no projection study on sugar beet production in Turkey has been conducted. As a result, the study intends to contribute to the literature by addressing this gap.

## REFERENCES

1. Akaike, H. 1974. A New Look at the Statistical Model Identification. *IEEE Trans. Automat. Contr.,* **19**(6): 716-723.
2. Akdag, M. and Yigit, V. 2016. Forecasting Inflation with Box-Jenkins and Artificial Neural Network Models. *Atatürk Üniv. İktisadi ve İdari Bilimler Derg.,* **30**(2): 269-283.
3. Akgul, I. 2003. Zaman Serilerinin Analizi ve ARIMA Modelleri, Der Yayınları, İstanbul.
4. Ataseven, B. 2013. Forecasting by Using Artificial Neural Networks. *Öneri Derg.,* **10**(39): 101-115.
5. Badmus, M. A. and Adepeju, O. 2011. Forecasting Cultivated Areas and Production of Maize in Nigerian Using ARIMA Model. *Asian J. Agric. Sci.,* **3(3):** 171-176.
6. Biswas, B., Dhaliwal, L. K., Singh, S. P. and Sandhu, S. K. 2014. Forecasting Wheat Production Using ARIMA Model in Punjab. *Int. J. Agric. Sci.,* **10**(1): 158-161.
7. Biswas, R. and Bhattacharyya, B. 2013. ARIMA Modelling to Forecast Area and Production of Rice in West Bengal. *J. Crop Weed,* **9(2):** 26-31.
8. Box, G. E. P. and Jenkins, G. M. 1970. *Time Series Analysis: Forecasting and Control*. Holden Day, San Francisco, CA.
9. Celik, S. 2019. Modelling and Estimation of Potato Production in Turkey with Time



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

Series Analysis. *Int. J. Trend Res.*, **6(5):** 111-116.
10. Chen, P., Yuan, H. and Shu, X. 2008. Forecasting Crime Using the ARIMA Model. *Fifth International Conference on Fuzzy Systems and Knowledge Discovery*, PP. 627-630.
11. Debnath, M. K., Bera, K. and Mishra, P. 2013. Forecasting Area, Production and Yield of Cotton in India Using ARIMA Model. *RRJoSST,* **2(1):** 16-20.
12. Elliott G., Rothenberg, T. J. and Stock, J. H. 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica,* **64**: 813-836.
13. Esturk, O. 2018. An Assessment on Importance and Future of the Sugar Industry in Turkey. *Anatol. J. Econ. Bus.,* **2**(1): 67-81.
14. Food and Agriculture Organization (FAO). 2022. Agricultural Production Data. Retrieved July 16, 2022 from: https://www.fao.org/faostat/en/#data/TCL.
15. geler.pdf.
16. Harlianingtyas, I., Salim, A., Hartatie, D. and Supriyadi, S. 2020. Forecasting sugarcane production in the Asembagus sugar factory. *IOP Conf. Ser: Earth Environ. Sci.,* **411(1):** 1-6.
17. Hossain, Md. M. and Abdulla, F. 2016. Forecasting Potato Production in Bangladesh by ARIMA Model. *JAS,* **1**(4): 191-198.
18. Iqbal, N., Bakhsh, K., Maqbool, A. and Ahmad, A. S. 2005. Use of the ARIMA model for Forecasting Wheat Area and Production in Pakistan. *J. Agric. Soc. Sci.,* **1(2):** 1813-2235.
19. Kaya, A. 2021. Türkiye Şeker Piyasası ve Uygulanan Politikalar (Sugar Market and Policies Applied in Turkey). *JAVStudies,* **7(4):** 429-437.
20. Khan, K, Khan, G., Shaikh, S. A., Lodhi, A. S. and Jilani, G. 2015. ARIMA Modelling for Forecasting of Rice Production: A Case Study of Pakistan. *Lasbela Univ. J. Sci. Technol.,* **4**: 117-120.
21. Kiran, B. 2014. *Time Series Analysis*. Lecture Notes, Distance Education Application and Research Center, Istanbul University.
22. Kumar, M. and Hasija Rajendra, R. C. 2017. ARIMA Modelling and Forecasting of Cotton Productivity in India. *Environ. Ecol.*, **35(1A):** 224-228.
23. Lumley, T., Diehr, P., Emerson, S. and Chen, L. 2002. The Importance of the Normality Assumption in Large Public Health Data Sets. *Annu. Rev. Public Health*, **23**:151-69.
24. Mishra, P., Ghazi Al Khatib, A. M., Sardar, I., Mohammed, J., Karakaya, K., Dash, A., Ray, M., Narsimhaiah, L. and Dubey, A., 2021. Modeling and Forecasting of Sugarcane Production in India. *Sugar Tech.,* **23(6):** 1317-1324.
25. Nath, B., Singh Dhakre, D. and Bhattacharya, D. 2019. Forecasting Wheat Production in India: An ARIMA Modelling Approach. *J. Pharmacogn. Phytochem.,* **8(1):** 2158-2165.
26. Ng, S. and Perron, P. 2001. Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Econometrica,* **69(6):** 1519-1554.
27. Paswan, S., Paul, A., Paul, A. and Noel, A. S. 2022. Time Series Prediction for Sugarcane Production in Bihar Using ARIMA & ANN model. *Pharma. Innov.,* **11(4):** 1947-1956.
28. Ramesh, D., Bhattacharyya, B. and Biswas, R. 2014. Forecasting of Maize Production in Andhra Pradesh by ARIMA modeling. *Environment & Ecology,* **32**(4B): 1709-1713.
29. Sahinli, M. A. 2021. Predicting and Analyzing of Turkish Sugar Price with ARCH, GARCH, EGARCH and ARIMA Methods. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development,* **21(3):**703-712.
30. Schwarz, G. 1978. Estimating the Dimension of a Model. *Ann. Stat.,* **6(2):** 461-464.
31. Schwert, G. W. 1989. Tests for Unit Roots: A Monte Carlo Investigation. *J. Bus. Econ. Stat.,* 7: 147-159.
32. Senturk, O. 2020. *Agricultural Products Market-Sugar Beet 2020*. Agricultural Economic and Policy Development Institute (TEPGE), Ministry of Agriculture and Forestry, Republic of Türkiye. Retrieved July 16, 2022 from: https://arastirma.tarimorman.gov.tr/tepge/Belgeler/Yay%C4%B1n%20Ar%C5%9Fivi/2017-2022%20Yay%C4%B1n%20Ar%C5%9Fivi/Yay%C4%B1nno328.pdf.



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]

33. Sharma, P. K., Dwivedi, S., Ali, L. and Arora, R. K. 2018. Forecasting Maize Production in India Using ARIMA Model. *AE*, **5(1):** 01-06.
34. Suresh, K. K. and Krishna Priya, S. R. 2011. Forecasting Sugarcane Yield of Tamilnadu Using ARIMA Models. *Sugar Tech*, **13**: 23-26.
35. TEPGE. 2021. *Agricultural Products Market-Sugar Beet*. Agricultural Economic and Policy Development Institute (TEPGE), Ministry of Agriculture and Forestry, Republic of Türkiye. Retrieved July 16, 2022 from: https://arastirma.tarimorman.gov.tr/tepge/Menu/27/Tarim-Urunleri-Piyasalari.
36. Tinni Chaudhuri, T., Verma, P. and Khetan, M. 2020. Modeling and Forecasting of Rice Production in Some Major States of India Using ARIMA. *IJRASET,* **8(12):** 749-757.
37. Turkish Statistical Institute (TSI). 2012. *Statistical Indicators 1923-2011*. Turkish Statistical Institute Printing Division,
41. 

Ankara. Retrieved July 16, 2022 from: https://teyit.fra1.cdn.digitaloceanspaces.com/wp-content/uploads/2019/11/istatistikgoster
38. TURKSEKER. 2020. *Sector Report 2020*. Retrieved July 16, 2022 from: https://www.turkseker.gov.tr/?ModulID=8&MenuI D=36.
39. Unsal, Y. 2022. *Ürün Raporu, Seker Pancarı*. Tarımsal Ekonomi ve Politika Geliştirme Enstitüsü. No: 354, Ankara. Retrieved January 06, 2023 from: https://arastirma.tarimorman.gov.tr/tepge/Belgeler/PDF%20%C3%9Cr%C3%BCn%20Raporlar%C4%B1/2022%20%C3%9Cr%C3%BCn%20Raporlar%C4%B1/%C5%9Eeker%20Pancar%C4%B1%20%C3%9Cr%C3%BCn%20Raporu-TEPGE-354.pdf.
40. Vishwajith K. P., Sahu, P. K., Dhekale, V. S. and Mishra, P. 2016. Modelling and Forecasting Sugarcane and Sugar Production in India. *IJED,* **12(1):** 71-79.

## پیش بینی تولید چغندرقند در ترکیه با استفاده از روش باکس جنکینز(Box-Jenkins)

**د. ساریکا**

## چکیده

ترکیه به دلیل آب وهوا و ویژگی‌های خاک، کشور مناسبی برای تولید چغندرقند است و در بین کشورهای تولیدکننده چغندرقند جایگاه قابل توجهی دارد. بنابراین، در این پژوهش، برای پیش‌بینی مقادیر تولید چغندرقند برای ترکیه طی ده سال آینده از یک میانگین متحرک یکپارچه اتورگرسیو (ARIMA) استفاده شد. موثرترین ساختار مدل [ ARIMA (2، 3،1] برای این منظور با استفاده از داده های ۱۹۲۵ تا ۲۰۲۰ ایجاد شد. سال‌های ۲۰۱۹ و ۲۰۲۰ به‌عنوان سال اعتبارسنجی مدل مورد استفاده قرار گرفتند. هنگامی که مقادیر مشاهده شده و مورد انتظار تولید چغندرقند با هم مقایسه شوند، داده ها نشان می دهد که مقادیر پیش بینی شده کمی کمتر از مقادیر واقعی است. همچنین نتایج نشان می دهد که تا سال ۲۰۳۰، تولید چغندرقند در ترکیه به ۲۰.۵ میلیون تن خواهد رسید. این تحقیق ممکن است به سیاستگذاران کمک کند تا برای ذخیره سازی، صادرات یا واردات چغندرقند برنامه ریزی کنند. همچنین با استفاده از این داده ها می توان از هدررفت منابع جلوگیری کرد.



[ Downloaded from jast.modares.ac.ir on 2024-05-16 ]

[ DOI: 10.22034/JAST.26.1.1 ]