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Analysis of Life Cycle Inventory Data of Pistachio Production through Cobb-Douglas Analogy and Forecasting with ARIMA Model

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Abstract: Pistachio production holds significant economic importance for Türkiye. This study analyzes the life cycle inventory (LCI) data of pistachio production by using the Cobb-Douglas production function, and utilizes the Cobb-Douglas function to examine the relationship between inputs (human labor, machinery, diesel fuel, fertilizers, chemicals and manure) and pistachio production output. Fertilizers and diesel fuel are recognized as the two most energy-intensive inputs, accounting for 65.3% of total energy use. Total energy input for pistachio production yields a value of 24583.34 MJ ha-1. The regression analysis indicates high R^2 values of 0.9998 for the first set of variables (human labor, machinery and diesel fuel) and 0.9763 for the second set (fertilizers, chemicals and manure), demonstrating a very strong correlation between the inputs and pistachio output, and the Cobb-Douglas production function fits the data extremely well. The Autoregressive Integrated Moving Average (ARIMA) model is employed to forecast pistachio production for the period 2023-2030, using annual pistachio production data from 1961 to 2022. The ARIMA(1, 2, 2) model is identified as the most suitable model for forecasting pistachio production in Türkiye, based on its optimal statistical performance. Forecasted pistachio production values generated using the ARIMA(1, 2, 2) model are in good agreement with historical trends for the pistachio production. The ARIMA(1, 2, 2) model predicts that pistachio production will exceed 270000 tons by 2030. The results of this study are expected to provide a guidance to pistachio producers and policymakers in making decisions for sustainable pistachio production.

Keywords: Pistachio, Life cycle inventory data analysis, Cobb-Douglas function, ARIMA model

INTRODUCTION

Pistachios are widely cultivated, particularly in the Mediterranean and Middle Eastern regions, and are recognized worldwide for their significant economic and nutritional value. The three leading countries in global pistachio production are the USA, Türkiye, and Iran (Uzundumlu et al., 2024). Pistachio production is also an important source of income for local economies and plays a vital role in international trade (Afshar et al., 2013; Külekçi and Aksoy, 2013). Human labor, machinery, fuel, fertilizers, chemicals and manure constitute the main stages of pistachio production (Sağlam et al., 2012). Each stage is critical for ensuring the efficiency and sustainability of the production process. Therefore, a comprehensive analysis and optimization of each agricultural stage are essential to enhance both the output and sustainability of pistachio production. Each stage is critical for ensuring the efficiency and sustainability of the production process. Therefore, a comprehensive analysis and optimization of each agricultural stage are essential to enhance both the output and sustainability of pistachio production.

The Life Cycle Inventory (LCI) analysis of agricultural products is critical for understanding their environmental impact. The integration of Cobb-Douglas production functions in LCI provides a robust framework for analyzing the relationship between input and output in agricultural systems. The use of the Cobb-Douglas analogy in LCI analysis allows for a deeper understanding of the input-output relationships in pistachio production. The LCI of perennial crops, including pistachios, highlights both the long-term environmental benefits and the challenges associated with pistachio cultivation (i Canals et al., 2007). By applying the Cobb-Douglas production function, it is possible to model the efficiency of resource use and the elasticity of production inputs, providing a comprehensive perspective on the sustainability of pistachio farming practices. In addition to LCI analysis, forecasting tools such as the

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Autoregressive Integrated Moving Average (ARIMA) model provide valuable insights into future pistachio production trends (Öztep and Işın, 2023).

The ARIMA model is widely used in agricultural research to forecast production levels, market demand and input requirements (Box et al., 2015). The ARIMA model has been successfully used to forecast the production of various nuts, including groundnuts (Celik et al., 2017), hazelnuts (Bars et al., 2018), walnuts (Başer et al., 2018), almonds (Say, 2024) and pistachios (Öztep and Işın, 2023) in Türkiye. It has also been used to forecast global pistachio production trends (Uzundumlu et al., 2024). The combination of LCI methodologies with Cobb-Douglas production functions provides valuable insights into the environmental impacts and resource efficiency in pistachio production (Brentrup et al., 2004; Coelli et al., 2005). Furthermore, the integration of these approaches with ARIMA model forecasts allows for a comprehensive assessment of current sustainability and future trends in pistachio production. Collectively, these methodologies provide a powerful framework for promoting sustainable and efficient pistachio production.

The objective of this study is to examine the impact of various inputs (human labor, machinery, diesel fuel, fertilizers, chemicals and manure) on the output of the pistachio production process and develop strategies or solutions for the optimal utilization of resources to improve production efficiency, using the Cobb-Douglas production function approach. Furthermore, the ARIMA model is utilized to forecast pistachio production trends for the period 2023-2030 based on historical pistachio production data.

MATERIALS and METHODS

Materials

Data on the impact of various inputs including human labor, machinery, diesel fuel, fertilizers, chemicals and manure on the output (yield per hectare) of the pistachio production were obtained from published literature (Saglam, et al., 2012; Afshar et al., 2013; Külekçi and Aksoy, 2013). These inputs were then converted into energy units using standard energy coefficients as defined by Pimentel (1992) and Singh et al. (2002).

Methods

Cobb-Douglas Function

The Cobb-Douglas production function was developed by American mathematician Charles Cobb and economist Paul Douglas in 1928 (Houthakker, 1955). It is one of the most widely used production functions in agricultural production studies, known for its simplicity, effectiveness and ability to incorporate multiple inputs (Singh et al., 2002). The Cobb-Douglas function represents a production process that combines multiple inputs to generate an output, and it is expressed as:

$$y_i = a_0 + \sum_{j=1}^{n} a_j(x_{ij}) + \exp(e_i) \qquad i = 1, 2, \ldots\ldots, n \tag{1}$$

where y_i = output, x_{ij} = inputs in the production process, a_0 = constant term, a_j = coefficients of the inputs estimated from the model and e_i = error term.

The natural logarithmic transformation to the production function yields the following (Afshar et al., 2013):

$$ln(y_i) = lna_0 + \sum_{j=1}^{n} a_j ln(x_{ij}) + e_i \qquad i = 1, 2, \ldots\ldots, n \tag{2}$$

The following equations (Eqs. 3 and 4) are used to determine the relationship between inputs and outputs in the pistachio production process:

$$ln(y_p) = lna_0 + a_1 lnx_1 + a_2 lnx_2 + a_3 lnx_3 + e_i \tag{3}$$

$$ln(y_p) = lna_0 + a_1 lnx_4 + a_2 lnx_5 + a_3 lnx_6 + e_i \tag{4}$$

where y_p = pistachio production output, and inputs correspond to x_1 = human labor, x_2 = machinery, x_3 = diesel fuel, x_4 = fertilizers, x_5 = chemicals and x_6 = manure.

Statistical analysis of the data was done with the Microsoft Excel (Microsoft 365, Microsoft Corporation, Washington DC, USA).

ARIMA Model

The ARIMA model is a robust parametric modeling method used in time series analysis, specifically developed to analyze non-stationary time series and make future forecasts (Wei, 2006). It was introduced by Box and Jenkins (1973), and is also known as the Box-Jenkins model. The modeling process involves identifying an appropriate ARIMA model, fitting it to historical data, and using it to generate short-term forecasts (Özdemir and Aksoy, 2024). The model is denoted as ARIMA (p, d, q), where p is the number of autoregressive (AR) terms or the number of lag observations (also known as the lag order or lags of the dependent variable) in the model, d is the number of differences needed to make the series stationary or the number of times the raw observations are differenced (also known as the degree of differencing) and q is the number of moving average (MA) terms or the size of the moving average window (also known as the order of the moving average or lags of the forecast errors) (Bars et al., 2018; Başer et al., 2018; Öztep and Işın, 2023; Özdemir and Aksoy, 2024; Say, 2024).

The stationarity of the time series data was evaluated using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). The order of differencing (d) was performed iteratively until the time series became stationary. The p-value obtained for the ADF test was found to be less than 0.05 (the significance level), inferring that the time series does not have a unit root and is stationary. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were analyzed to identify appropriate values for the moving average (q) and autoregressive (p) parameters, respectively.

Akaike Information Criterion (AIC) and Schwartz's Bayesian Information Criterion (BIC) criteria were used to determine the most appropriate ARIMA model (Akaike, 1974; Schwarz, 1978). These criteria balance the complexity of the model with its fit and allow the most appropriate model to be selected (Burnham and Anderson, 2002). Low AIC and BIC values indicated that the model fitted the data better (Akaike, 1974; Schwarz, 1978). The parameters of the ARIMA(p, d, q) model identified were estimated using the maximum likelihood estimation method, recognized as one of the most reliable approaches for parameter estimation in ARIMA modeling (Box et al., 2015).

The adequacy of the model was checked by examining the residuals to ensure that the residuals were randomly distributed and uncorrelated (Ozdemir et al., 2008). The ARIMA(p, d, q) model selected was then employed to forecast pistachio production in Türkiye for the period 2023-2030, using annual pistachio production data from 1961 to 2022 (FAOSTAT, 2023). Data analysis was carried out using Python software (version 3.12.10, Python Software Foundation, Beaverton, OR, USA).

RESULTS and DISCUSSION

The primary energy inputs considered in this study included human labor, machinery, diesel fuel, fertilizers, chemicals and manure. The Cobb-Douglas production function was applied to assess the contribution of each input to pistachio production. Energy consumption for each input was quantified in megajoules per hectare (MJ ha-1), and the total energy input was determined by summing the average energy values of all inputs (Table 1).

Human labor accounted for an average energy equivalent of 1026.15 MJ ha-1, representing approximately 4.2% of the total energy input, primarily used for harvesting, pruning and land preparation. Machinery usage contributed an average of 1859.49 MJ ha-1 (7.6%), mainly associated with land preparation, fertilizer application and pest control. Diesel fuel had a significantly higher average energy equivalent of 6874.21 MJ ha-1, constituting 27.9% of the total input, and was primarily consumed in machinery operation and irrigation.

Fertilizer application resulted in the highest energy consumption, with an average of 9196.98 MJ ha-1 (37.4%). Among fertilizers, nitrogen-based fertilizers were the most energy-intensive, accounting for 17% of the total energy input. Chemicals, including herbicides, pesticides and fungicides, constituted an average energy equivalent of 4350.56 MJ ha-1, accounting for about 17.7% of the total energy input. Manure contributed an average of 1275.95 MJ ha-1, approximately 5.2% of the total energy input.

The total energy input for pistachio production was calculated as 24583.34 MJ ha-1. Fertilizers and diesel fuel were identified as the two most energy-intensive inputs, together accounting for 65.3% of total energy use. These findings highlight the need for improved input efficiency. Strategies such as increasing the use of organic fertilizers and transitioning to renewable energy sources such as biofuels, biogas or electricity from solar and wind could reduce both energy consumption and the environmental impact of pistachio production.

The results of the regression analysis showed high R^2 values of 0.9998 for the first set of variables (human labor, machinery and diesel fuel) and 0.9763 for the second set (fertilizers, chemicals and manure), indicating a very strong correlation between the inputs and pistachio output. These high R^2 values suggest that the Cobb-Douglas production function fits the data extremely well, and is highly effective in explaining the variability in pistachio output, with fertilizers and diesel fuel identified as the most influential inputs.

Table 1. *Energy equivalents of inputs and their shares in pistachio production*

Inputs	Energy equivalent (MJ ha^{-1})	Ratio (%)
Human labor	1026.15	4.2
Machinery	1859.49	7.6
Diesel fuel	6874.21	27.9
Fertilizers	9196.98	37.4
Chemicals	4350.56	17.7
Manure	1275.95	5.2
Total	24583.34	100

Forecasting pistachio production is an essential tool for analyzing annual pistachio production output and planning allocation of resources. In this study, pistachio production trends in Türkiye were forecasted using an appropriate ARIMA model based on historical pistachio production data. Initially, the data were subjected to the ADF test to assess stationarity. The test results indicated that stationarity was achieved at the second difference level of the time series, suggesting this as the most suitable form for modeling.

ACF and PACF plots were constructed to identify p and q values for the ARIMA model (Figure 1). The ACF plot showed significant correlations at lag 1 (adjacent) and lag 2 (near adjacent) observations with a gradual decline at higher lags. The PACF plot revealed a strong correlation at lag 1 with a sharp drop in subsequent lags, indicating potential autoregressive behavior. The blue region in both plots represents the 95% confidence interval, meaning that anything within the blue area is statistically close to zero, whereas anything outside the blue area is statistically non-zero.

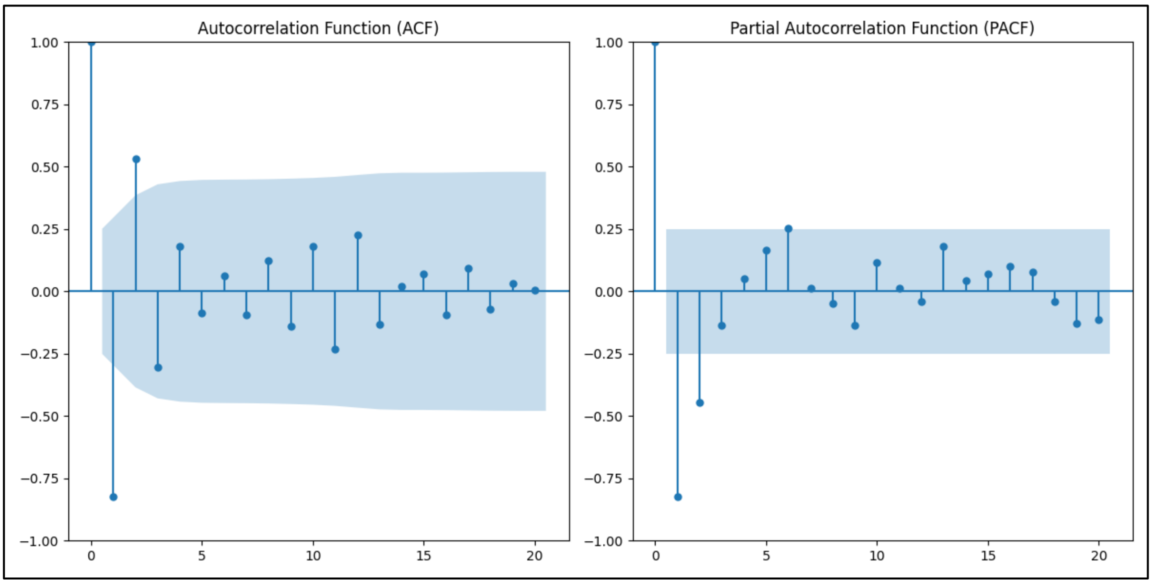

Figure 1. *ACF and PACF plots of the second differences of the time series*

The most appropriate model for the second differences of the time series was identified as ARIMA(1, 2, 2) model, which yielded the lowest AIC and BIC values, indicating the best fit. Pistachio production in Türkiye was forecasted using the ARIMA(1, 2, 2) model for the period 2023-2030 based on pistachio production data from 1961 to 2022 (Figure 2). Historical data revealed a long-term upward trend in pistachio production, driven by factors such as the expansion of cultivation areas, technological advancements and improved agricultural practices. Despite this overall growth, substantial fluctuations were also evident. Peaks in pistachio production corresponding to the years such as those in 1991, 2018 and 2020 were followed by sharp declines, reflecting vulnerabilities to external influences like climate variability, pest outbreaks and economic conditions. The record-high production of over 296000 tons in 2020 serves as a benchmark for assessing the system’s performance under favorable conditions.

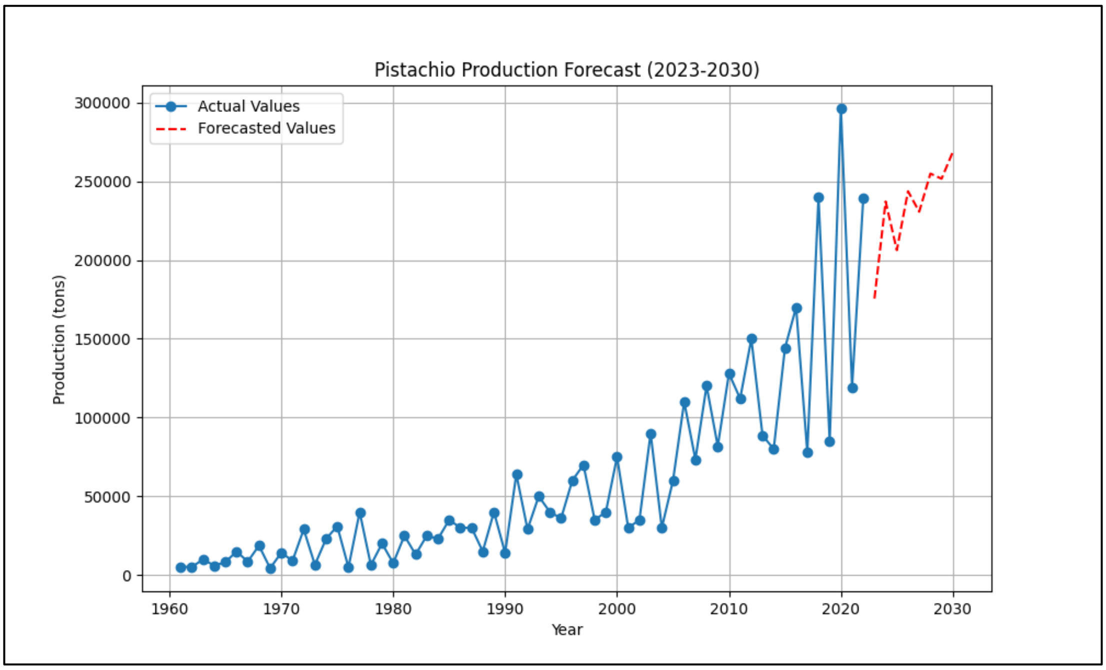

Figure 2. *Pistachio production data from 1961 to 2022 (FAOSTAT, 2023), along with forecasted values for the years 2023 to 2030*

Forecasted pistachio production values generated using the ARIMA model aligned well with historical trends for the pistachio production showing up and down trends annually through the end of the forecast period. These up and down trends can be attributed to the periodicity observed in pistachio production (Öztep and Işın, 2023). However, the periodicity effect is foreseen to decrease over the years, as reflected in the forecasted values through 2030. Although this analysis highlights the importance of time series forecasting in agricultural planning, it is also essential to recognize that long-term forecasts inherently involve uncertainty, and should be reinforced with considerations of environmental, economic and agricultural factors. The identified trend indicates that the upward increase in pistachio production, particularly evident after 2020, is expected to continue, provided there are no unforeseen disruptions such as climate change, pest outbreaks or economic crises. These forecasts offer valuable insights for strategic decision-making, including market demand analysis, export potential evaluation and efficient resource management.

As time progresses, the impact of production fluctuations appears to diminish, indicating the potential for a more stable and sustainable growth rate in pistachio production in the coming years. However, it is important to note that these forecasts are sensitive to environmental, economic and agricultural factors. Based on the fitted growth trend, pistachio production in Türkiye is projected to exceed 270000 tons by 2030. This projected increase is attributed to factors such as favorable climatic conditions, technological advancements in agricultural practices and the implementation of effective agricultural policies in pistachio production. With the adoption of sustainability-oriented strategies and sound agricultural policies, Türkiye has the potential to become one of the leading countries in the global pistachio market. In this context, agricultural planning and forecasting-based approaches for pistachio production are expected to play a crucial role in minimizing production fluctuations and supporting long-term, sustainable growth.

CONCLUSION

The Cobb-Douglas analysis revealed that key inputs, particularly fertilizers and diesel fuel, have a significant influence on pistachio production, as evidenced by high R^2 values (> 0.97). This indicates a strong fit between the model and the data, suggesting that optimizing these inputs can effectively improve pistachio production. The study also highlights the importance of sustainable energy-use strategies in pistachio cultivation. Overreliance on synthetic fertilizers and fossil fuels can lead to environmental problems and diminishing returns. Therefore, the adoption of organic fertilizers, improved machinery efficiency and the use of renewable energy sources such as biofuel, biogas, and solar and wind power is recommended to enhance both sustainability and cost-effectiveness. By optimizing resource use and adopting sustainable practices, pistachio growers can improve both pistachio production and energy efficiency. ARIMA-based forecasts project that Türkiye's pistachio production could exceed 270000 tons by 2030.

The findings of this study have important implications for policymakers and pistachio growers. At the policy level, promoting sustainable input use such as incentivizing organic fertilizers, supporting the adoption of renewable energy technologies and training for efficient resource management can drastically enhance pistachio production. Integrating these insights into farm management strategies can lead to improved profitability, reduced environmental impact and greater resilience against external shocks such as market fluctuations and climate variability. With the adoption of appropriate policies and sustainable management practices, Türkiye has the potential to become a global leader in pistachio production.

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AUTHOR CONTRIBUTIONS

The authors contributed equally to this study.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

Afshar, R. K., Alipour, A., Hashemi, M., Jovini, M. A., & Pimentel, D. (2013). Energy inputs-yield relationship and sensitivity analysis of pistachio (Pistacia vera L.) production in Markazi Region of Iran. Spanish Journal of Agricultural Research, 11(3), 661-669. https://doi.org/10.5424/sjar/2013113-3877

Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19(6), 716-723. https://doi.org/10.1109/TAC.1974.1100

Bars, T., Uçum, İ., & Akbay, C. (2018). ARIMA modeli ile Türkiye fındık üretim projeksiyonu. Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 21, 154-160. https://doi.org/10.18016/ksutarimdoga.v21i41625.473029

Başer, U., Bozoğlu, M., Eroğlu, N. A., & Topuz, B. K. (2018). Forecasting chestnut production and export of Turkey using ARIMA model. Turkish Journal of Forecasting, 2(2), 27-33. https://doi.org/10.34110/forecasting.482789

Box, G. E., & Jenkins, G. M. (1973). Some comments on a paper by Chatfield and Prothero and on a review by Kendall. Journal of the Royal Statistical Society. Series A (General), 136(3), 337-352. https://www.jstor.org/stable/2344995?seq=1

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time Series Analysis: Forecasting and Control. 5th Edition. John Wiley and Sons, Hoboken, NJ, USA.

Brentrup, F., Küsters, J., Kuhlmann, H., & Lammel, J. (2004). Environmental impact assessment of agricultural production systems using the life cycle assessment methodology: I. Theoretical concept of a LCA method tailored to crop production. European Journal of Agronomy, 20(3), 247-264. https://doi.org/10.1016/S1161-0301(03)00024-8

Burnham, K. P., & Anderson, D. R. (2002). Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. 2nd Edition. Springer Science and Business Media, New York, NY, USA.

Celik, S., Karadas, K., & Eyduran, E. (2017). Forecasting the production of groundnut in Turkey using ARIMA model. The Journal of Animal and Plant Sciences, 27(3), 920-928.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). An Introduction to Efficiency and Productivity Analysis. 2nd Edition. Springer Science and Business Media, New York, NY, USA.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427-431. https://doi.org/10.2307/2286348

FAOSTAT (2023). Crops and livestock products domain. Retrieved November 3, 2024, from https://www.fao.org/faostat/en/#data/QCL

Houthakker, H. S. (1955). The Pareto distribution and the Cobb-Douglas production function in activity analysis. The Review of Economic Studies, 23(1), 27-31. https://doi.org/10.2307/2296148

i Canals, L. M., Romanya, J., & Cowell, S. J. (2007). Method for assessing impacts on life support functions (LSF) related to the use of 'fertile land' in Life Cycle Assessment (LCA). Journal of Cleaner Production, 15(15), 1426-1440. https://doi.org/10.1016/j.jclepro.2006.05.005

Külekçi, M., & Aksoy, A. (2013). Input–output energy analysis in pistachio production of Turkey. Environmental Progress and Sustainable Energy, 32(1), 128-133. https://doi.org/10.1002/ep.10613

Ozdemir, M., Ozen, B. F., Dock, L. L., & Floros, J. D. (2008). Optimization of osmotic dehydration of diced green peppers by response surface methodology. LWT-Food Science and Technology, 41(10), 2044-2050. https://doi.org/10.1016/j.lwt.2008.01.010

Özdemir, F., & Aksoy, A. (2024). Pistachio production quantity estimate 2022–2030: Evidence from leading countries and Türkiye using the ARIMA model. Applied Fruit Science, 66(6), 2269-2277. https://doi.org/10.1007/s10341-024-01198-2

Öztep, R., & Işın, F. (2023). ARMA modeli ile Türkiye Antep fıstığı üretimi tahmini. Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 26(4), 878-887. https://doi.org/10.18016/ksutarimdoga.vi.1163930

Pimentel, D. (1992). Energy inputs in production agriculture. Energy in farm production. In Energy in World Agriculture, Vol. 6, pp. 13-29, Fluck, R. C. Editor. Elsevier, Amsterdam, The Netherlands. https://doi.org/10.1016/b978-0-444-88681-1.50007-7

Python (2025). Python for Windows, version 3.12.10, Python Software Foundation, Beaverton, OR, USA.

Sağlam, C., Tobi, I., Küp, F., & Çevik, M. Y. (2012). An input-output energy analysis in pistachio nut production: A case study for Southeastern Anotolia Region of Turkey. African Journal of Biotechnology, 11(8), 1868-1871. https://doi.org/10.5897/AJB11.2296

Say, A. (2024). Badem üretiminde verimlilik ve sürdürülebilirlik: Projeksiyon temelli bir yaklaşım. Journal of Agriculture, 7(2), 177-183. https://doi.org/10.46876/ja.1603578

Schwarz, G. (1978). Estimating the dimension of a model. The Annals of Statistics, 6(2), 461-464. https://doi.org/10.1214/aos/1176344136

Singh, H., Mishra, D., & Nahar, N. M. (2002). Energy use pattern in production agriculture of a typical village in arid zone, India—part I. Energy Conversion and Management, 43(16), 2275-2286. https://doi.org/10.1016/s0196-8904(01)00161-3

Uzundumlu, A. S., Pınar, V., Tosun, N. E., & Kumbasaroğlu, H. (2024). Global pistachio production forecasts for 2020–2025. Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 27(5), 1105-1115. https://doi.org/10.18016/ksutarimdoga.vi.1397897

Wei, W. W. S. (2006). Time Series Analysis: Univariate and Multivariate Methods. 2nd edition. Pearson Education, New York, NY, USA.