Forecasting Turkey's Hazelnut Export Quantities with Facebook's Prophet Algorithm and Box-Cox Transformation

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Abstract

Time series forecasting methods are used by an evolving field of data analytics for the prediction of market trends, sales, and demands. Turkey is the major producer of hazelnut in the world. If Turkey wants to continue its domination of hazelnut and protect the price-setting role, time series forecasting methods could be key factors accordingly. There are a few studies that focused on time series forecasting of hazelnut export quantities of Turkey, and this study uses a recently developed algorithm and implements a power transformation to increase the forecast accuracy. The presented research aims to forecast Turkey's hazelnut export quantities for the coming 36-months starting from June 2020. The forecasting process was conducted with the help of Facebook's Prophet algorithm. To improve the forecast accuracy, a Box-Cox power transformation was also implemented to process. To find out the stationarity and periodicity of the data set, the Augmented Dickey-Fuller test and autocorrelation function was applied to the time-series data. The Prophet algorithm, with Box-Cox transformation, projected the hazelnut export quantity could be over five hundred thousand tons from 07/2020 to 06/2023. The export quantities were in an increment trend, and the slope of the trend has increased since June 2008 by 0.66 % per month. The Prophet algorithm also revealed the seasonality of the data set, and the export amounts indicate monthly oscillations. The monthly export volumes start to increase and reach their peak value in October because August is the time for the harvest of hazelnuts in Turkey.

Keywords : Box-Cox transformation, forecasting, hazelnut, Prophet, time series

1. Introduction

Time series forecasting is a statistical method based on past values of the data to predict future values with the least predictable error is an essential area of research (Bhardwaj et al., 2020). For decades it was used in many fields ranging from predicting the behavior of financial markets to accurate energy load prediction (Passalis et al., 2020). Time series forecasting can be conducted with stochastic models such as autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) or seasonal autoregressive integrated moving average (SARIMA) or with artificial neural networks such as seasonal artificial neural networks (SANN) or time-lagged neural networks (TLNN). Support vector machines (SVMs) also can be used to forecast time series data (Adhikari and Agrawal, 2013). In the last decade, Facebook also created a software named Prophet for forecasting time series that are of interest in Facebook (Papacharalampous and Tyralis, 2020). The Prophet application programming interface (API) is open-source software released by Facebook's Core Data Science team (Facebook, 2020). The Prophet is a fast and quite interpretable machine learning method in which non-linear trends are fit with yearly, weekly, and daily seasonality as well as holiday effects to fit the smoothing and forecasting functions. (Zhao et al., 2018, Park et al., 2019, Papacharalampous and Tyralis, 2020). It also excels at processing daily periodicity data with large outliers and shifts in trends and can model multiple periods of seasonality simultaneously (Zhao et al., 2018). Many time series forecasting studies were conducted using Prophet. Erinjeri et al. (2020) studied the reduction of unplanned late hours in inpatient procedure scheduling, Park et al. (2019) has conducted time series analysis and forecasting daily emergency department visits and Zhao et al. (2018) studied day-of-week and seasonal patterns of PM 2.5 concentrations over the United States with this algorithm.

Power transformations are parametric, monotonous transformations that are used to make data more Gaussian-like. These techniques are useful for modeling problems related to heteroscedasticity or other conditions where normality is required and have, for a long time, been used in many applications (Carroll and Ruppert, 1981, Gonçalves and Meddahi, 2011). Several transformation methods have been used to fulfill the data sets to Gaussian base criteria (Howarth and Earle, 1979). Log transformation, square-root transformation, reciprocal transformation, inverse transformation, arcsine transformation, and Box-Cox transformation (BCT) are examples of power transform methods (Osborne, 2010). Box-Cox transformation has been thoroughly researched and extended to several various data processing scenarios. Economics, econometrics, statistics, medicine, system dynamics modeling, and prediction, and time series forecasting are among these research areas (Bicego and Baldo, 2016). Peng et al. (2019) conducted a study to assess expanded comfort in outdoor urban public spaces using BCT. He et al. (2019) forecasted energy consumption in Anhui province of China, and Meloun et al. (2005) analyzed soil cores polluted with certain metals using the Box-Cox transformation.

Hazelnut (Corylus avellana L.) is one of the popular and commonly consumed tree nuts belonging to the Betulaceae family (Taş et al., 2019). Hazelnuts are preferred for their valuable nutrients, sterols, phytochemicals, micronutrients, essential minerals, and B-complex vitamins (Onal-Ulusoy et al., 2019). As a primary raw material in chocolate, confectionery, and bakery, it has significant importance for the food industry (Çetinbaş-Genç et al., 2019, Hoşgün et al., 2017). More than 1 million tons of hazelnut were produced worldwide in 2017. The major producers are Turkey, Italy, and Azerbaijan, with shares of 65 %, 13 %, and 4 %, respectively (Tunçil, 2020). In the last five years, the worldwide planted hazelnut field has intensively grown, reaching 670,000 ha in 2017. Besides, as farmers in the Southern Hemisphere began planting new hazelnut orchards, hazelnut production recently spread beyond the natural range of the crop, i.e., Europe and Western Asia (Ascari et al., 2020). Turkey is the biggest producer in the world, with about 675,000 tons of in-shell hazelnuts (Celenk et al., 2020). Hazelnut is a strategic crop for Turkey in terms of cultivated acreage, related employment, and economic assets (Sen et al., 2019). The Black Sea region is the mainland of hazelnut cultivation areas in Turkey. The hazelnut sector contributes to the economy of the area by providing substantial employment opportunities in factories (Acaröz Candan et al., 2019). Hazelnut orchards are located in the northern latitudes at 36-41°, 30 km inland from the coastal regions, and in places not exceeding 0.75 – 1 km in height. While in 33 cities, there are hazelnut-growing zones, only 16 are permitted for the processing of commercial hazelnuts (Şenol and Zenk, 2020). Turkey's annual hazelnut production is shown in Fig. 1 (TUIK, 2019). The phenomenon known as alternate bearing could also be observed in Fig. 1 for hazelnut productivity. Depending on their Phyto-gerontology, perennial fruit crops produce plenty of fruits ('On' crop) in one year and fewer fruits ('Off' crop) in the following year (Sharma et al., 2019).

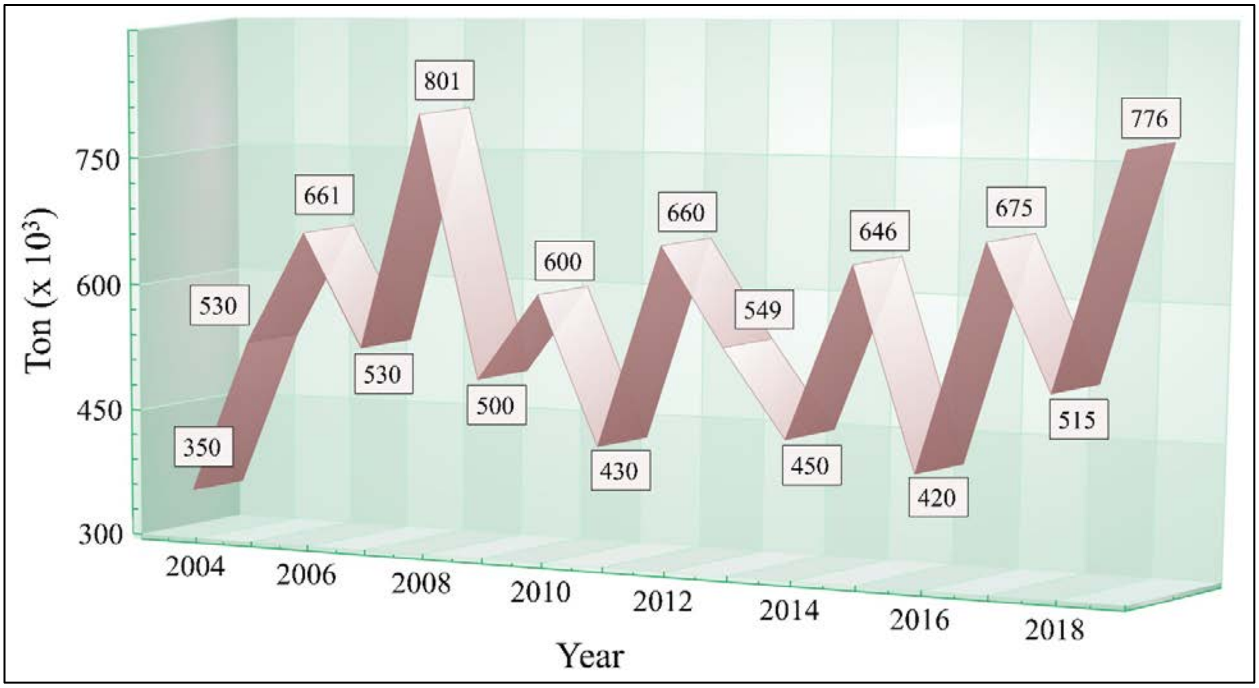

Figure 1. Annual hazelnut production of Turkey

This study was conducted to forecast Turkey's hazelnut export quantities with Facebook's Prophet algorithm for the next 36 months. A Box-Cox transformation was also applied to the data set for further improvement of the forecasting accuracy.

2. Data and Methods

The hazelnut export data gathered from Trade Map website (Trade-Map, 2020). The data includes the products with numbers 080221 and 080222. The monthly hazelnut export quantities and incomes of Turkey and hazelnut prices per kg from January 2002 to May 2020 can be seen in Figure 2.

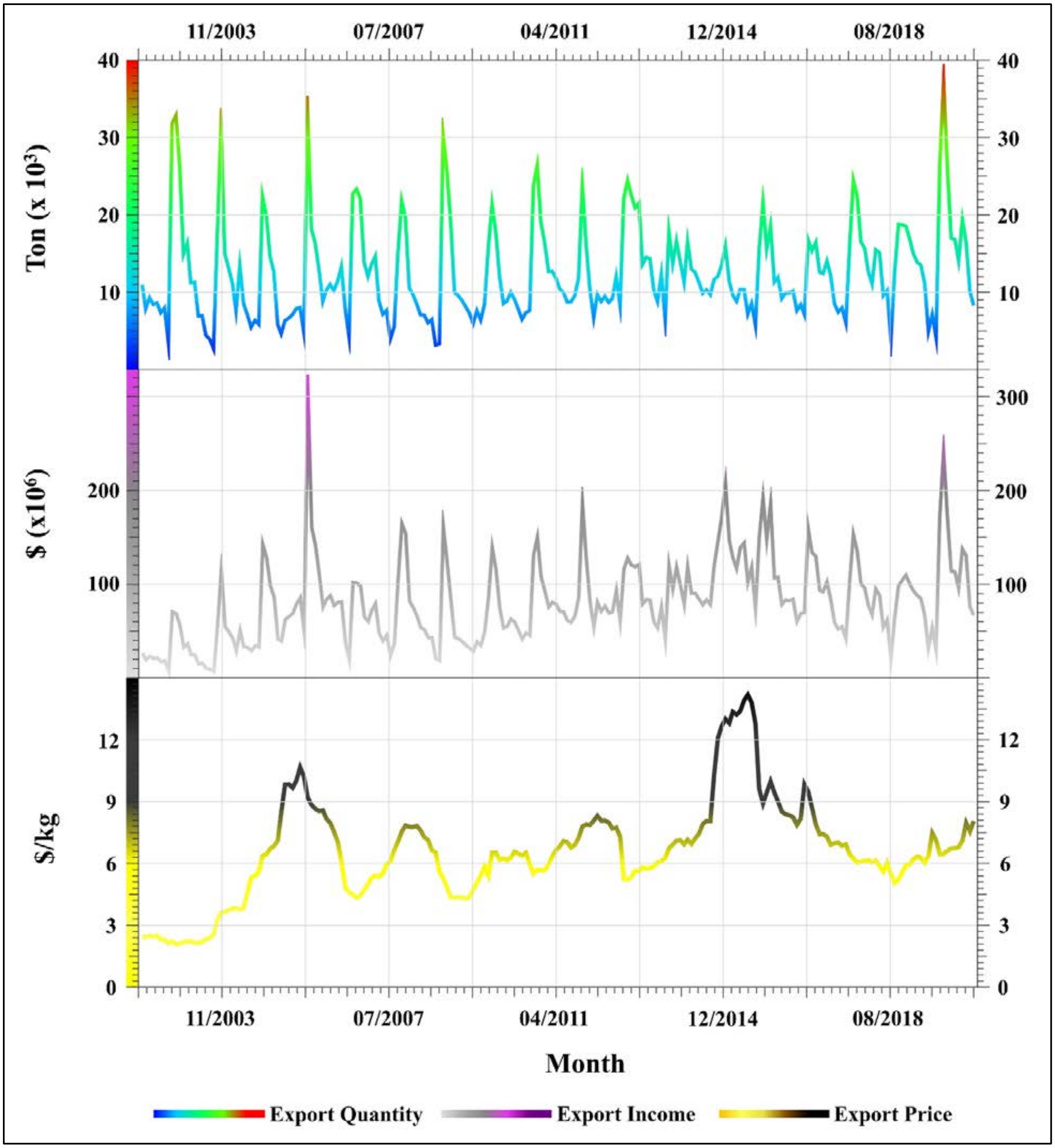

Figure 2. Turkey's hazelnut export datum

When forecasting time series data, there are assumptions that the summary statistics of observations are consistent. The first important point is whether the data is stationary or not because a stationary time series easily be modeled (Ruppert and Matteson, 2015). A time-series data is stationary if the distribution of $\{X_t, \dots \dots, X_{t+n}\}$ is the same as that of $\{X_{t+k}, \dots \dots, X_{t+n+k}\}$ for any choice of t, n, and k. This means that as time passes, the series does not drift away from its mean value (Heiberger and Holland, 2015). In the study, the stationarity of the data set was checked with the Augmented Dickey-Fuller (ADF) unit root test. ADF is one of the more widely used unit root tests to distinguish between stationary and nonstationary series (Cryer and Chan, 2008).

The second important thing is the periodicity (frequency) of the time series data. The dominant frequency was calculated by the autocorrelation function (ACF) in this research. The analysis of autocorrelation is a useful tool for finding repeating patterns. Given data, Y_1, Y_2, ..., Y_N at time t_1, t_2, ..., t_N, autocorrelation function (ρ_k) for a variety of lags k = 1, 2,…., n can be defined as in Eq. (1).

$$\rho_k = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{1}$$

Where, $\bar{Y}$ is the mean of the dataset (Cryer and Chan, 2008). At least 50 observations are required to give a reliable estimate of the ACF, and the individual sample autocorrelations should be calculated up to lag k, where k is about T/4 (Brockwell and Davis, 2016).

Forecasting of hazelnut export values was conducted with Facebook's Prophet API in Python. The Prophet is an open-source algorithm created by the Core Data Science Team of Facebook. This software is based on two concepts. The first concept is that it is developed over many iterations of forecasting a variety of data at Facebook. The second one is that it helps analysts to make incremental improvements by checking the model manually with a system for measuring and tracking forecast accuracy and flagging forecasts. Prophet was developed as a decomposable time series model that has three main model components: trend, seasonality, and holidays. These components can be expressed as in Eq. (2).

$$y(t) = g(t) + s(t) + h(t) + \in_t \tag{2}$$

Here, $g(t)$ is the trend function, $s(t)$ represents the periodic changes, $h(t)$ represents the effects of holidays and $\in_t$ is the error term. More details about the Prophet API can be found in Taylor and Letham (2017).

For further improvement of forecasting accuracy, a Box-Cox transformation was applied to the data set. BCT has long been accepted as an efficient way to achieve well-specified models with symmetric errors and consistent variances of error (Taylor, 2017). Box-Cox transformation is a way of converting non-normal variables into a standard form. Lambda (λ) coefficient identified by this transformation indicates the power to which all data should be created (Voyant et al. 2020). The BCT is often applied to time series data to obtain variance stability, Gaussianity of the distribution function, and additive seasonality (Fructuoso da Costa and Fernando Crepaldi, 2014). The basic formulation of the Box-Cox transform is given in Eq. [3], which transforms a given variable x into $x^{(\lambda)}$for x > 0 (Bicego and Baldo, 2016);

$$x^{(\lambda)} = \begin{cases} \frac{x^{\lambda}-1}{\lambda} & if\ \lambda \neq 0 \\ \log(x) & i\ f\ \lambda = 0 \end{cases} \tag{3}$$

The scipy.stats Python module provides a built-in Box-Cox transformation method. This module evaluates a set of lambda coefficients (λ) and selects the value that achieves the best approximation of normality (Scipy, 2020).

The prediction accuracy of the Prophet is evaluated with the mean absolute percentage error (MAPE) and mean absolute error (MAE) values. MAPE is commonly used as a measure of the accuracy of forecasts because it represents error as a percentage and can thus be used in model analyses of various datasets and can be calculated as in Eq. (4).

$$MAPE = \frac{1}{n}\sum_{x=1}^{n}\frac{|g(x)-y|}{|y|} \tag{4}$$

where, n is the number of data instances, x is the vector of explanatory variables, y is the target variable, and g is a regression model (de Myttenaere et al., 2016).

2. Results and Discussions

3.1.Stationarity Test

An Augmented Dickey-Fuller unit root test was performed to understand whether the time series is stationary or not. A rejection of the null hypothesis (H0) in ADF means that the time series has to be a mean zero stationary series, and it does not have a time-dependent structure. It is advisable to use a relatively high significance (*p*-value) level, such as 5 %, to reject the null hypothesis (Neusser, 2016). The ADF test was performed with Python, and the descriptive data can be seen in Table 1.

Table 1. Descriptive data for stationarity analysis

ADF Statistics	*p*-value	Critical Values		
		1 %	5 %	10 %
-2.944536	0.040409	-3.462	-2.876	-2.574

As can be seen in Table 1, the p-value ≤ 0.05, which means we reject the null hypothesis (H0), the data does not have a unit root and is stationary.

2.2. Periodicity Test

The periodicity of the data was determined with the autocorrelation function. The ACF plot obtained for k = 55 is shown below (Fig. 3) and proved that the dataset shows significant oscillations in every 12 months.

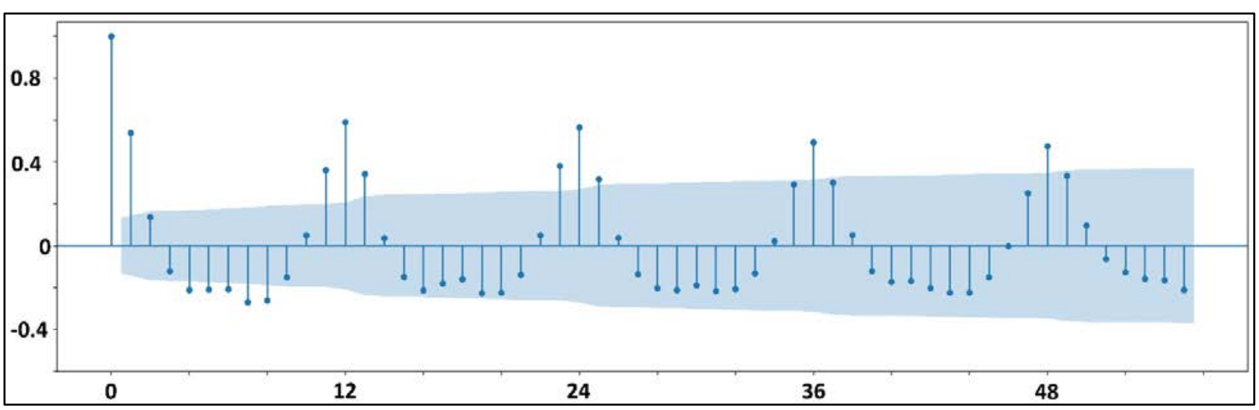

Figure 3. ACF plot of the time-series data

2.3. Forecasting the Hazelnut Export Quantities with Prophet and Box-Cox Transformation

The forecasting process has some assumptions and limitations. First of all, the Prophet algorithm only fits the best curve to the past data, applying a linear or logistic curve and Fourier coefficients for the seasonal components. This model assumes that the patterns in the past can be seen in the future so that the average magnitude and scale of predicted pattern transitions is the same as found in history. The most important limitation of the model is if the dataset is highly irregular, the algorithm will not give good forecasting. Also, this API cannot take account of exogenous factors that influence the time series, and the dataset needs to be pre-defined formatted before starting the prediction. The forecasting process was conducted primarily with the measurement of the quality of the forecast. In order to understand the modeling accuracy, the first 198 months were used for training, and the last 24 months were used for testing. The predictions for testing data using Prophet with and without Box-Cox transformation can be seen in Fig. 4, and the accuracy of the forecast results with MAE and MAPE values can be seen in Table 2, respectively. The selected λ value by scipy.stats.boxcox module that achieves the best approximation of normality was 0.036458.

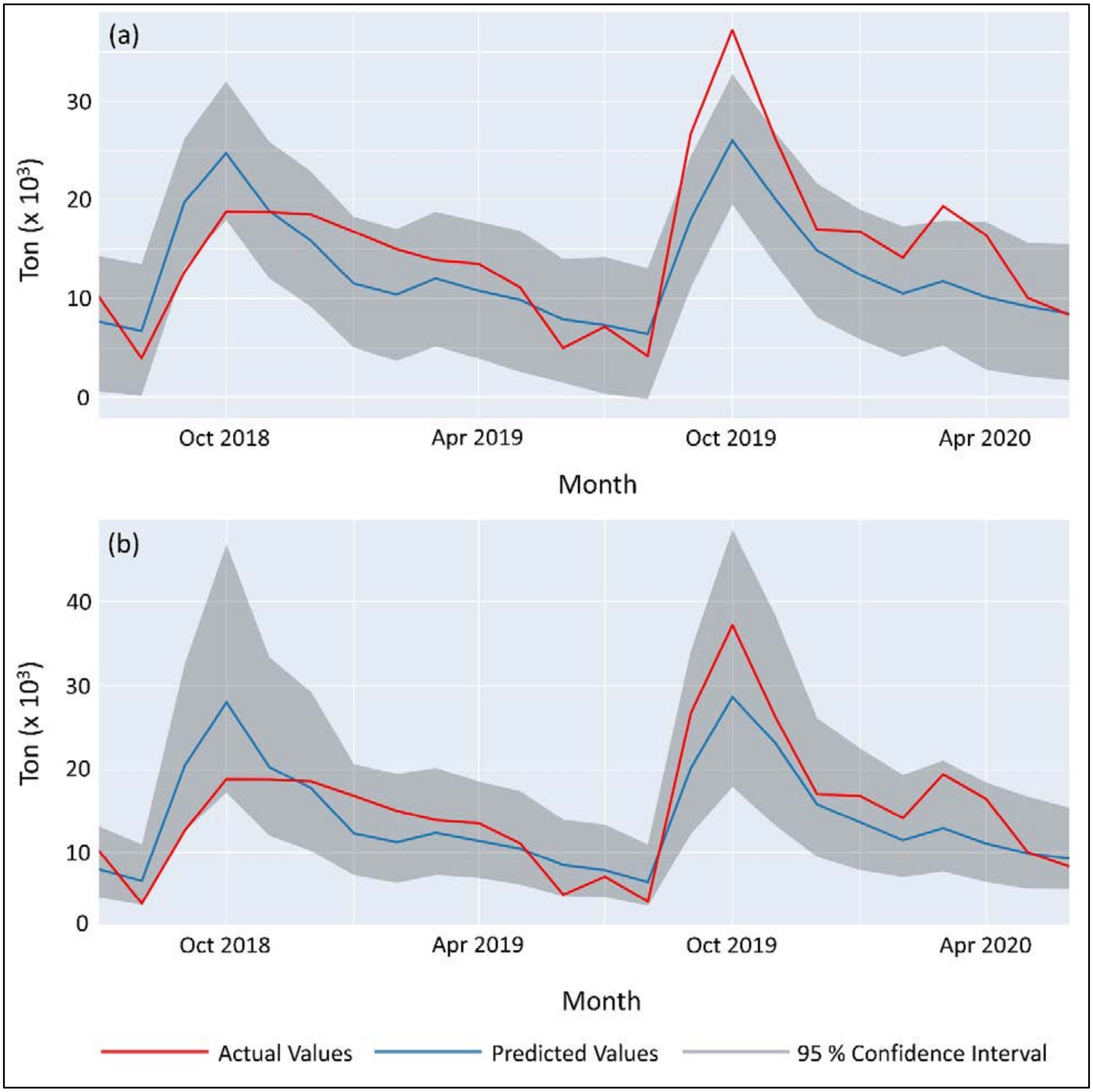

Figure 4. Measurement of the quality of the forecast on testing data with (a) no transformation and (b) Box-Cox transformation

Table 2. Accuracy measures for predictions

Accuracy Measure	No Transformation	With Box-Cox Transformation
MAE	3883	3394
MAPE	27.37	25.74

The Box-Cox transformation process enhanced the accuracy of the model by 1.63 %. The Lewis scale of interpretation of estimation accuracy indicates that a MAPE value less than 10% can be considered highly accurate, 11% - 20% as good, 21 % - 50% as reasonable, and 51% or more as inaccurate (Tefek et al., 2019). Considering both the MAPE value (25.74 %) and the actual values remain within the 95% confidence interval range, the Prophet algorithm made a good prediction that is close to good performance according to the Lewis scale, and the process continued with forecasting of export quantities with Box-Cox transformation for the next 36-months. Fig. 5 shows the projection of the Prophet model.

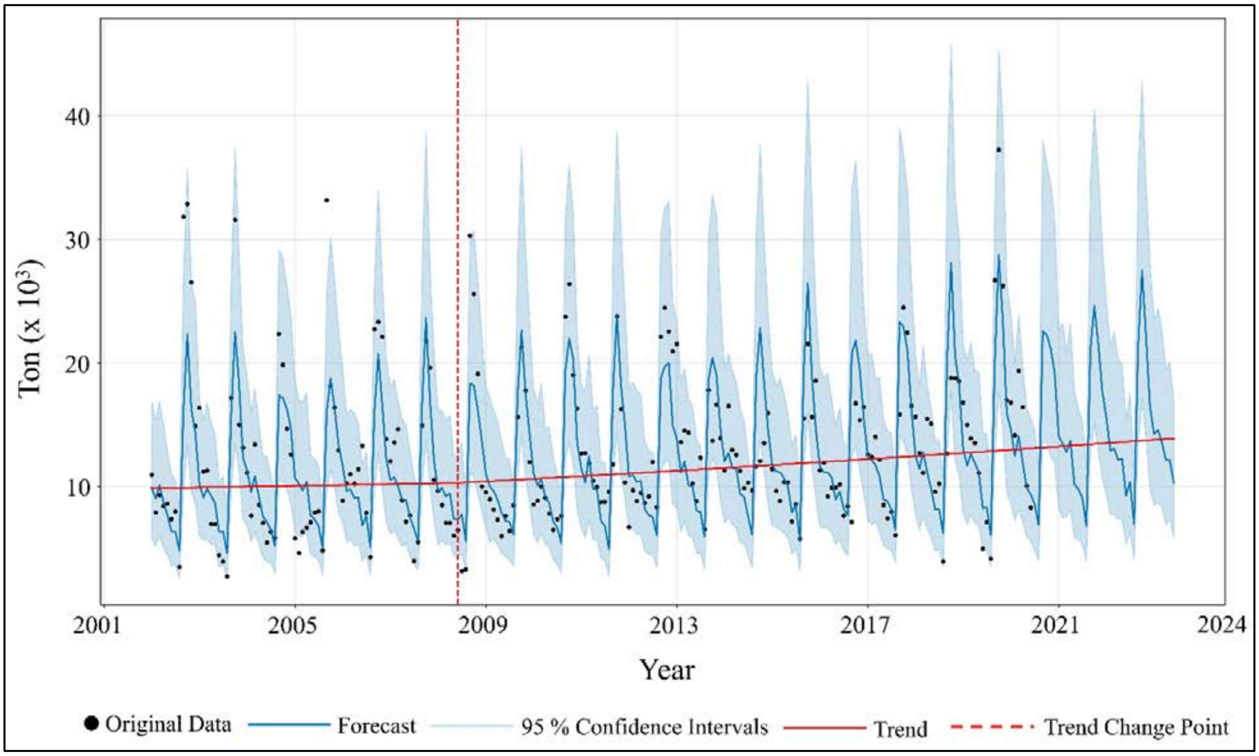

Figure 5. Forecast of the Prophet algorithm

According to the Prophet's projection, in June 2023, Turkey's hazelnut exports could be in the range of 6155 – 16795 tons in 95 % confidence interval, and the most expected value is 10302 tons. This value corresponds to an increase of 24.27 % compared to June 2020. Depending on this prediction, the expected quantity of hazelnut export for the next three years was found to be over five hundred thousand tons. The minimum, maximum, and most expected export amounts predicted by Prophet for the next three years are given in the table below.

Table 3. The Prophet's prediction of minimum, maximum, and most expected export amounts for the coming three years

	Period		
	07/2020 – 06/2021	**07/2021 – 06/2022**	**07/2022 – 06/2023**
Minimum (Ton)	104100	104425	107818
Maximum (Ton)	291949	286854	300293
Most Expected (Ton)	174768	176002	181702

When Table 3 is examined, it seems likely that the maximum export amount that could be between 07/2021 - 06/2022 will exceed the amount by 43.5% exported between 07/2019 - 06/2020 which was 203427 tons. Again, the lowest expected export amount for the same period could be 11 % less than the export amount between 07/2019 - 06/2020. It is predicted that the export volumes will continue to increase for the next 3 periods depending on the most expected values. While the export increase between 07/2021 - 06/2022 is projected as 0.7 % compared to 07/2020 - 06/2021, the export increase between 07/2022 - 06/2023 is estimated as ~ 4% compared to 07/2020 - 06/2021 period. These fluctuations between periods may depend on both the Phyto-gerontology and the increase in hazelnut fields.

The Prophet algorithm also provides the trend and the change point of the time series. The horizontal continuous red line in the figure represents the trend, and the vertical dashed red line represents the chancing point of the data set. When Fig. 5 is examined, there is an ascending trend in the export quantities. But the changing point highlighted that the trend increased its momentum in 2008 June with a change of 0.66 % per month since then. The trend change in June 2008 indicates that the hazelnut demand has increased since this date. Fig. 6 shows all the trend changes in the entire data set.

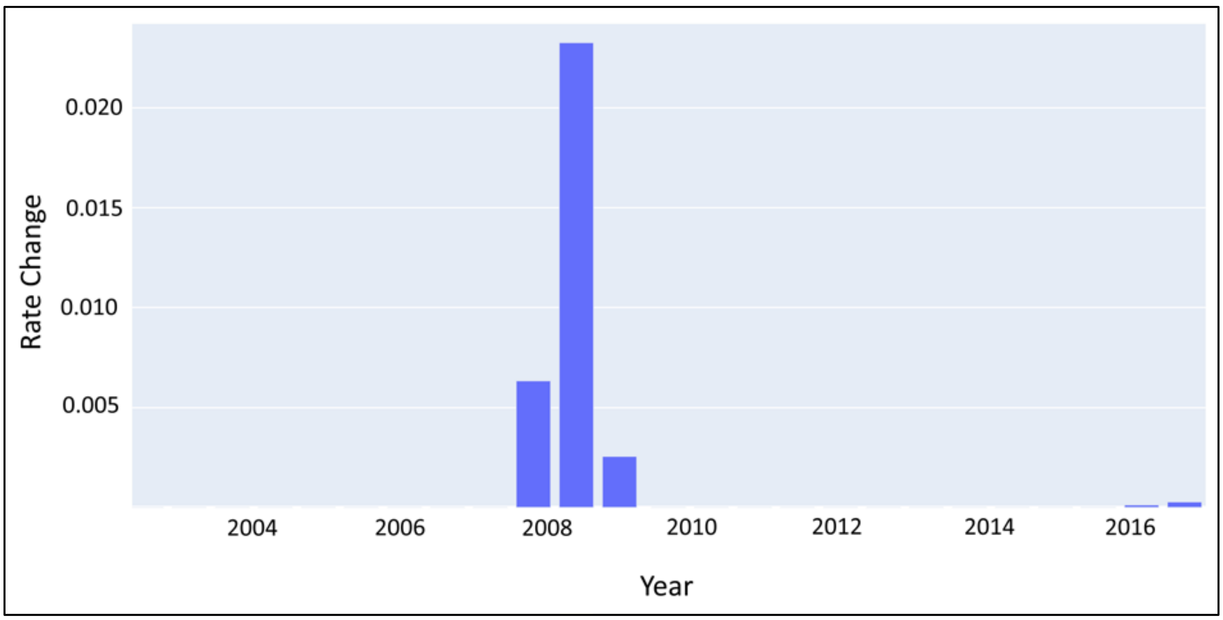

Figure 6. Trend change points in export quantities

As can be seen in Fig. 6. the most significant trend change was observed in June 2008, as mentioned before. However, four minor trend changes were detected in the export quantities in November 2007 with a rate change of 0.006, January 2009 with a rate change of 0.0021, and low rate change values in 2016. One of the most striking points in Fig. 5 was seasonal oscillations in annual hazelnut export amounts. A box plot was sketched to find out the seasonality of the export amounts, and can be seen in Fig. 7.

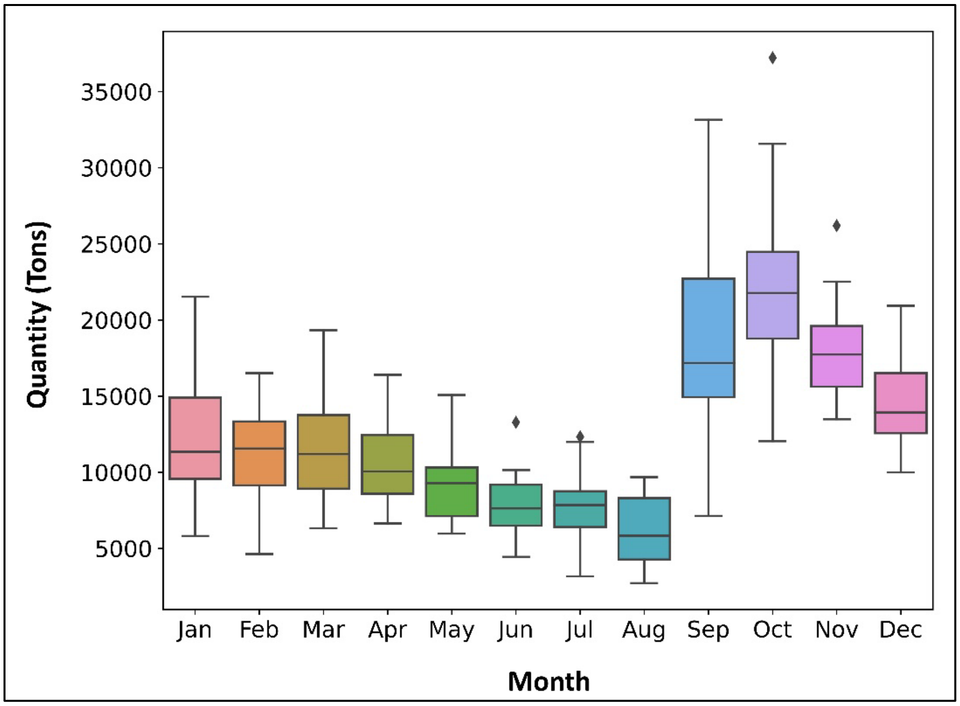

Figure 7. Yearly seasonality of hazelnut export quantities

Fig. 7 indicated that at the beginning of September, Turkey's hazelnut export quantity starts to increase and reaches its peak value in October. The reason for this situation is because August is the time for the harvest of hazelnuts in Turkey (Ramos Castro and Swart, 2017). The lowest export amount was observed in August. While Turkey's hazelnut production has a major impact on world hazelnut prices, it also affects the world's exports. Turkey's hazelnut yield per unit area to maintain its dominance in world production is of great importance. The area of hazelnut orchards in Turkey has increased by 12 % between 2004 – 2019 from 655000 ha to 734 000 ha (TUIK, 2019). For this reason, it is essential for Turkey to carry out both quality and quantity in hazelnut production. It is also important to conduct studies to determine the production levels of hazelnuts by making estimates of future export amounts for Turkey to be the country that determines the price of hazelnuts in the world. With the projections of annual hazelnut export volumes of this study, some issues such as increasing the yield, renewing the hazelnut orchards that have completed their economic life, finding new markets, maintenance of hazelnut fields, and incentives for producers can be handled by policymakers and thereby Turkey's economic gain can be increased. In addition, the results of this study may be a guide to hazelnut producers and to the researchers working on hazelnut. The results obtained with Prophet API predicted that the increasing trend in the export amounts of hazelnuts would continue in the medium term, and the outcomes of the study pioneers the necessary studies to prevent manufacturers from being harmed by this situation.

Conclusions

Time series forecasting is an essential field in all areas of science and engineering because these models can account for what might happen in the future and helps scientists and analysts to develop their goals and objectives. Time series forecasting is a technique that analyzes data and the sequence of time to predict future events. As seen in the literature, many methods have been developed for time series forecasting. Facebook's Prophet API is a powerful time-series forecasting tool because is fast and provides completely automated forecasts that can be tuned by hand by researchers. This study was carried out to forecast Turkey's hazelnut export in the next 36 months with Prophet starting from June 2020. A Box-Cox power transformation was applied to the data to improve the accuracy of the forecast. Box-Cox transformation enhanced the accuracy of the model by 1.63 %. According to Prophet's prediction between 07/2022 – 06/2023, the export quantities of hazelnut may rise to 300293 tons (upper bond of confidence interval), which corresponds to a rise of 47.6 %. The total hazelnut export for the next three years was found to be 532472 tons. The trend line showed an upward trend in export quantities and this upward trend has increased since June 2008. Besides, a box plot was sketched to find out the seasonality of the data set. The box plot indicates that at the beginning of September, hazelnut export quantity starts to increase because August is the time for the harvest of hazelnuts in Turkey. Being the leader in the production of hazelnut and hazelnut export in the world for Turkey is of great importance in economical aspect. This study is essential in terms of estimating the hazelnut export quantities for policymakers, hazelnuts employees and nut producers.

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