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Forecasting Figs Production in Turkey: A Historical Analysis from 1961 to 2021 by Using the Application Arima Model

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Abstract: *This research focuses on predicting the figs production in Turkey from 1961 to 2021 using the ARIMA (0,1,3) model. Figs play a significant role in Turkish agriculture, and accurate predictions can offer valuable insights for production planning, market analysis, and policy development. The historical production data is analyzed using the ARIMA (0,1,3) model to generate forecasts. Furthermore, the study examines the projected increase in figs production specifically for the year 2031. By extrapolating the observed trends and patterns in the past data, the study presents forecasts for figs production in 2031. These projections provide an estimate of the potential growth or changes in figs production, assisting stakeholders in decision-making and strategic planning within the figs industry. The findings of this study enhance our understanding of the future prospects for figs production in Turkey and can guide investments, resource allocation, and market strategies in the upcoming years.*

Keywords: Forecasting, Figs Production, Turkey, Arima (0,1,3),

1. INTRODUCTION

Figs hold immense historical and cultural significance in Turkey, playing a vital role in the country's agricultural sector. Turkey's favorable climate and geography make it a prominent global producer of figs. Accurately predicting fig production is crucial for effective agricultural resource management, supply chain logistics, and market forecasting (Karadeniz et.al,2015).

The objective of this study is to forecast fig production in Turkey from 1961 to 2021 using the ARIMA model. By analyzing historical fig production data through this model, we can gain valuable insights into production trends, identify factors influencing production, and make informed predictions for future fig production levels (Uysal and Güler, 2017).

Having a comprehensive understanding of historical fig production trends is vital for sustainable agricultural practices, optimizing resource allocation, and managing risks associated with production fluctuations. This study aims to contribute to the existing knowledge on fig production in Turkey and provide valuable insights for stakeholders in the agricultural industry (Işık et.al,2017).

The subsequent sections will discuss the methodology employed for the analysis, encompassing data collection, preprocessing, model specification, parameter estimation, and model fitting. We will present the results of the BSTS model, comparing the predicted fig production values with the observed data. Finally, we will delve into the implications of the findings and explore potential factors that may have influenced fig production in Turkey during the study period (Bozkurt and Öz, 2017).

One potential concern for fig production in Turkey is the possibility of reduced yield due to adverse weather conditions or climate change. Accurately forecasting fig production empowers stakeholders to make informed decisions, plan for market demands, and develop strategies for sustainable fig cultivation in Turkey (Karaman, and Yildiz, 2014).

2. METHODOLOGY

2.1. DATA COOLECT AND ANALYSIS

We obtained data from international databases, including FAOSTAT (Food and Agriculture Organization Statistical Database), and utilized SPSS software to apply the ARIMA model.

The ARIMA model, short for Autoregressive Integrated Moving Average, is a widely used time series forecasting model that predicts future values based on past observations. It consists of three main components: autoregression (AR), differencing (I), and moving average (MA) (Uzun and Gürbüz,2018).

Autoregression (AR) captures the dependency of the current value on previous values in the time series. It assumes that future values can be linearly modeled based on past values. The "p" parameter represents the number of lagged observations considered in the model. The AR component, denoted as AR(p), is expressed by the following equation:

$$y(t) = c + \varphi\text{^}1\, y(t-1) + \varphi\text{^}2\, y(t-2) + \ldots + \varphi_{\mathrm{p}}\, y(t-p) + \varepsilon(t) \ldots (2.1)$$

Here, y(t) represents the value at time t, c is a constant term, φ_1, φ_2, ..., φ_p are the autoregressive coefficients, and ε(t) is the error term at time t.

Differencing (I) is used to make the time series stationary by eliminating trends or seasonality. It involves taking the difference between consecutive observations to stabilize the mean and remove non-stationarity. The differencing component, denoted as I(d), is expressed as:

$$\Delta y(t) = y(t) - y(t-1) \ldots (2.2)$$

Here, Δy(t) represents the differenced series, and y(t) is the original series at time t. The differencing is performed d times until the series becomes stationary (Demirci et, al.2019).

Moving Average (MA) considers the influence of past error terms on the current value. It represents the weighted sum of previous error terms. The "q" parameter represents the number of lagged error terms used in the model. The MA component, denoted as MA(q), is expressed by the following equation:

$$y(t) = c + \theta\text{^}1\, \varepsilon(t-1) + \theta\text{^}2\, \varepsilon(t-2) + \ldots + \theta_{\mathrm{p}}\, \varepsilon(t-q) + \varepsilon(t) \ldots (2.3)$$

Here, ε(t) represents the error term at time t, and θ_1, θ_2, ..., θ_p are the moving average coefficients.

The ARIMA model combines these three components and is represented as ARIMA(p, d, q). The values of p, d, and q are chosen based on the specific time series and can be determined using techniques such as autocorrelation and partial autocorrelation plots.

The model is fitted to the historical data, and the estimated coefficients are used to make predictions for future time points. The accuracy of the ARIMA model relies on selecting appropriate values for p, d, and q, which can be determined through analyses such as autocorrelation and partial autocorrelation plots (Köksal and Kafa,2018).

2.2. BOX-LJUNG TEST APPROACH

The Box-Jenkins approach, developed by George Box and Gwilym Jenkins in the 1970s, is a widely used and popular technique for analyzing and forecasting time series data.

The Box-Jenkins approach involves a systematic three-step process, which includes model identification, model estimation and diagnostic checking, and model forecasting.

1. Model Identification: In the first step, an appropriate model is identified for the time series data. This is done by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots help determine the order of autoregressive (AR) and moving average (MA) components in the model. Based on the observed patterns in the plots, an initial model specification is chosen.

2. Model Estimation and Diagnostic Checking: Once the initial model is identified, the next step is to estimate the parameters of the model. This is typically done using maximum likelihood estimation or another suitable method. After estimating the model, diagnostic checks are performed to assess the adequacy of the chosen model. Residual analysis is conducted to identify any remaining patterns or lack of fit in the model. If the model does not meet the necessary assumptions or exhibits inadequate fit, adjustments are made by iteratively modifying the model specification and re-estimating the parameters until a satisfactory model is obtained.

3. Model Forecasting: Once a final model is selected and validated, it can be used to generate forecasts for future time periods. The model is applied to the available data to make predictions, and the accuracy of the forecasts is evaluated using various statistical measures.

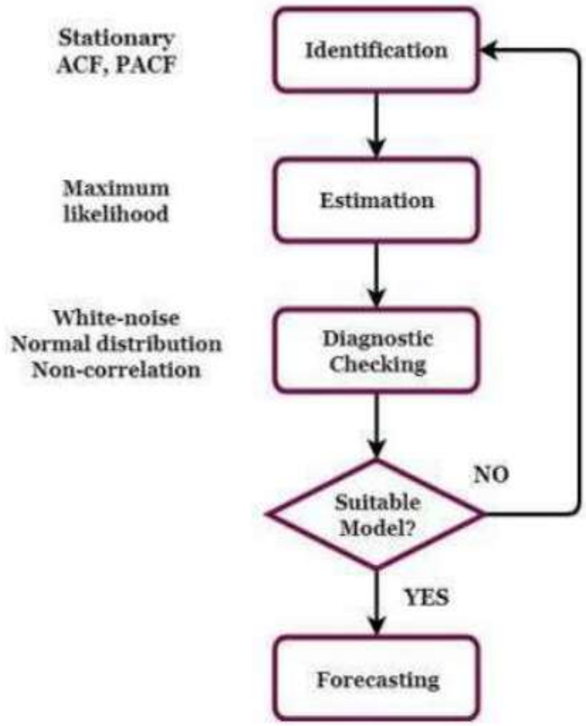

Figure 3. 1. Box- Jenkins procedure (Jahanshahi et al., 2019)

3. RESULTS AND DISCUSSION

3.1 APPLICATION OF ARIMA ON FIGS PRODUCTION TIME SERIES

IDENTIFICATION

Descriptive statistics offer a concise summary of important characteristics within a dataset. Based on the provided table of figs production in Turkey from 1961 to 2021, the descriptive statistics are as follows:

1. Mean: The mean, or average, represents the central tendency or typical value of the dataset. In this case, the mean figs production in Turkey from 1961 to 2021 is 258,136.33 tons.
2. Standard Deviation: The standard deviation measures the dispersion or variability of the dataset around the mean. A higher standard deviation indicates a wider range of values. For figs production in Turkey, the standard deviation is 51,750.953 tons, indicating a relatively significant variation in production levels.
3. Minimum: In this case, the minimum figs production recorded in Turkey during the specified period is 156,350 tons. This value represents the lowest recorded production level.
4. Maximum: For figs production in Turkey, the maximum recorded production level during the specified period is 370,000 tons. This value indicates the highest recorded production level.

Table 3.1. Descriptive Statistics of figs production

Mean	258136.33 **(tons)**
Std. Deviation	51750.953
Minimum	156350 **(tons)**
Maximum	370000 **(tons)**

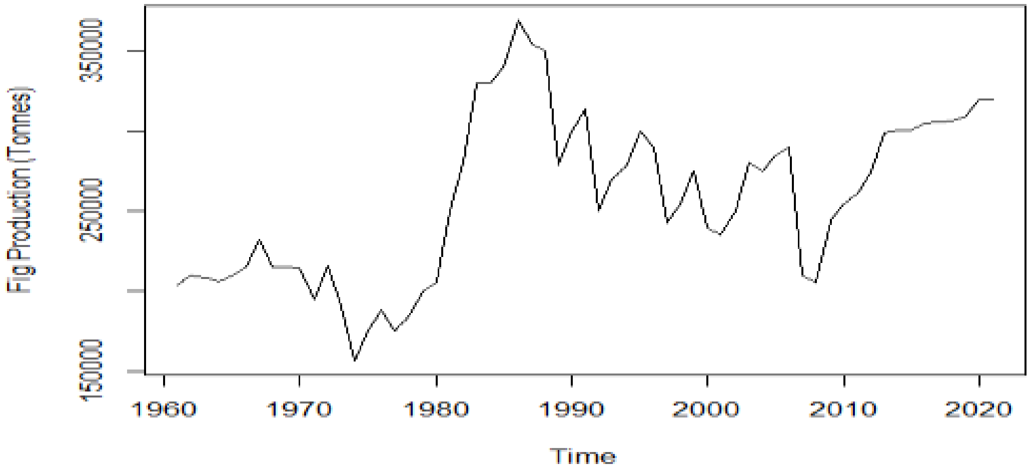

Figure 3. 1. Figs production in Turkey from 1961 to 2021

The differenced data was subjected to the Augmented Dickey-Fuller (ADF) test twice, and the test yielded a p-value of 0.012. This p-value indicates that, at a significance level of 5%, the differenced data can be considered stationary.

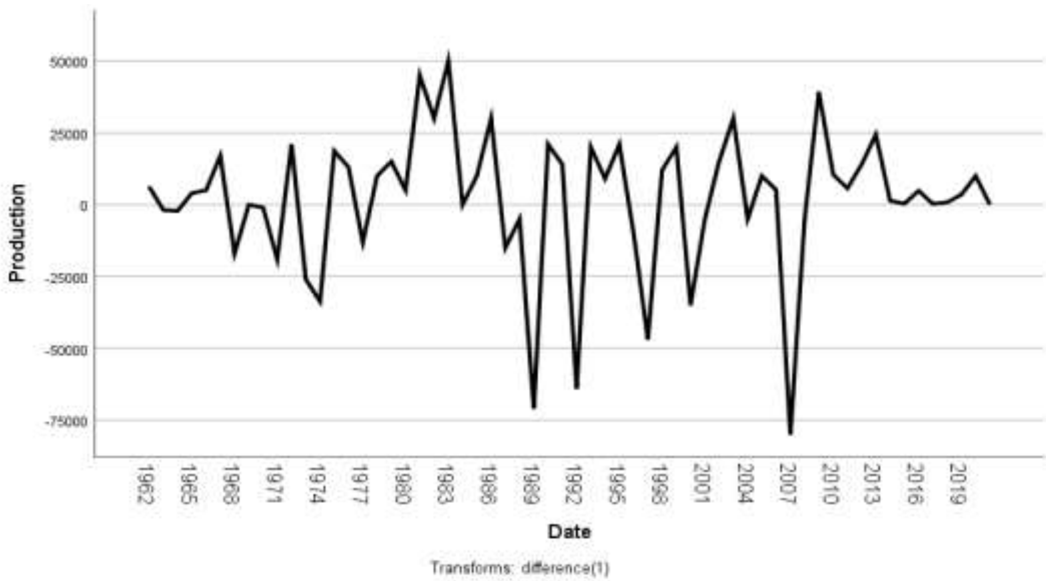

Figure 3. 2. Time series plot of figs production in Turkey after one differencing

ACF (Autocorrelation Function)

The autocorrelation function (ACF) plot displays the relationship between the observations of the "figs" variable and its past observations at different time lags. When the ACF plot shows a strong correlation at a specific lag, it indicates that the data follows a repeating pattern at that particular lag. This information assists in determining the order of the autoregressive (AR) term in the ARIMA model.

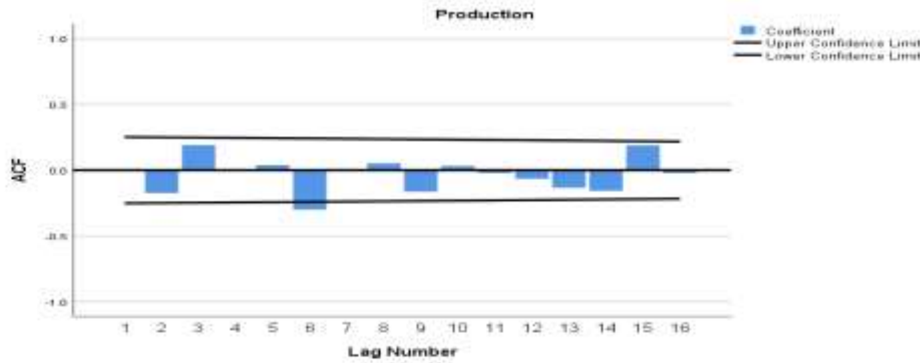

Figure 3.3. Autocorrelation Function for figs time series

PACF (Partial Autocorrelation Function)

The partial autocorrelation function (PACF) plot represents the partial autocorrelation function of a time series, which reveals the correlation between observations at different lags while taking into account the influence of intervening observations. This plot is particularly helpful in determining the order of the moving average (MA) term in an ARIMA model. By examining the PACF plot, one can observe the correlation between each observation and its lagged values, providing insights into the appropriate order of the MA term.

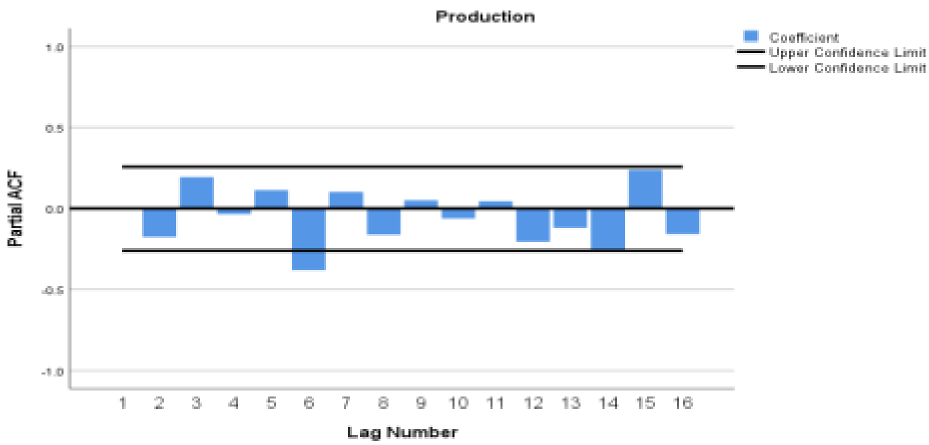

Figure 3. 4. Partial Autocorrelation Function for figs time series

ESTIMATION (SELECT FIT MODEL)

After ensuring the time series data has been transformed to be stationary in terms of mean and variance, the next step is to choose a suitable model by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) and observing their patterns. In this case, it was determined that the ARIMA (0,1,3) model provides the best forecast for figs production in Turkey. This conclusion is supported by the findings presented in Tables 3.2 and 3.3. The estimated model demonstrates both statistical significance overall and for its individual parameters, indicating its suitability for forecasting figs production accurately.

Table 3.2. ARIMA (0,1,3) model parameters

VARIABLES	ESTIMATE	SE	T-VALUE	P-VALUE
Constant	1895.267	3719.615	0.510	0.612
MA1	-0.191	0.126	-1.515	0.135
MA2	0.291	0.123	2.354	0.022
MA3	-0.394	0.127	-3.110	0.003

Table 3. 3. ARIMA (01,3) performance

RMSE	MAPE	MAE	AIC
22563.625	6.286	15765.523	1378.33

Figure 3. 5. Predicted value and actual values of cherry production time series by using ARIMA (0,1,3)

DIGNOSES (CHECK ERRORS)

The final step in evaluating the ARIMA (0,1,3) model for figs production involves conducting the Box-Pierce test to assess the model's accuracy and the residual autocorrelation test to detect any autocorrelation. The Box-Pierce test yields a p-value of 0.674, which is significantly greater than the significance level of 0.05. This indicates that the residuals exhibit characteristics of white noise and do not possess any significant autocorrelation. Consequently, the ARIMA (0,1,3) model is considered the most appropriate fit for the figs production data, as it successfully passes all diagnostic tests. However, despite being the optimal model, Figure 4.6 reveals that the predicted values align closely with the actual values, indicating a convergence toward the actual values series.

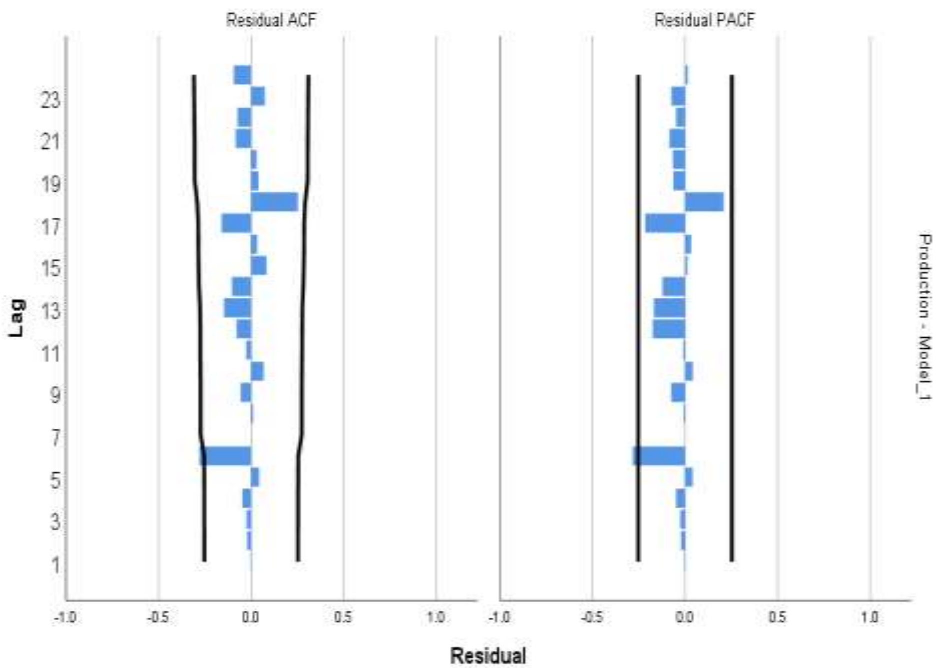

Figure 3. 6. Residual for ACF AND PACF (0, 1, 3)

FORECAST

The table presents a comparison between the actual values and predicted values of figs production from 2012 to 2021. It displays the recorded production numbers alongside the forecasted values for each corresponding year.

Table 3. 4. The actual and predicted values of figs production in 2012 to 2021

NO	DATE	ACTULE	FORECAST

1	2012	274535	322276
2	2013	298914	326263
3	2014	300282	328130
4	2015	300600	330026
5	2016	305450	331921
6	2017	305689	333816
7	2018	306499	335712
8	2019	310000	337607
9	2010	320000	339502
10	2021	320000	341397

Additionally, the ARIMA (0,1,3) model was employed to predict the figs production value in Turkey for the year 2021. As depicted in Figure 3.6, the plot reveals a similarity between the predicted values and the actual values for 2021. Specifically, it shows that the predicted values tend to align and converge with the actual values series.

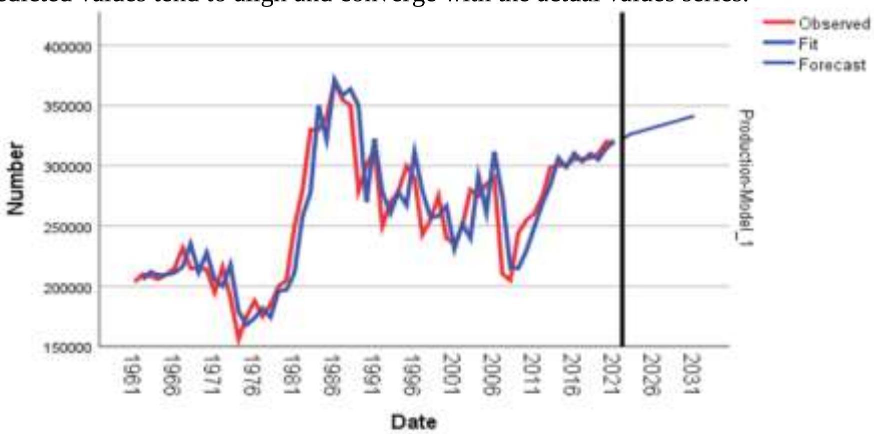

Figure 3.6. Predicted values of figs production in 2021

DISCUSSION

The results obtained from the ARIMA model reveal a promising outlook for figs production in Turkey, indicating a potential increase in production until the year 2031. These projections offer valuable insights for stakeholders involved in the figs production industry, enabling them to make informed decisions and allocate resources effectively. The forecasted growth in figs production presents numerous opportunities and implications (Akbulut, and Demirci, 2019).

Farmers can utilize these forecasts to optimize their cultivation practices, such as adjusting planting schedules, implementing advanced irrigation methods, or expanding their fig orchards in alignment with the projected demand. These proactive measures can significantly enhance productivity and profitability within the figs production sector.

Policymakers can leverage the forecasts to develop strategic plans and policies that support the sustainable growth of the figs industry in Turkey. This may involve providing incentives to fig farmers, investing in research and development for improved fig varieties, and implementing marketing initiatives to promote fig consumption both domestically and internationally.

Moreover, the projected increase in figs production can contribute to overall economic growth and open up new export opportunities for Turkey. By capitalizing on its competitive advantage in fig production, the country can expand its market share on a global scale and strengthen its position as a major supplier of figs.

However, it is crucial to consider potential challenges and uncertainties that may impact the forecasted increase in figs production. Factors like climate change, disease outbreaks, or market fluctuations can influence actual production levels. Therefore, it is imperative to continuously monitor and adapt the forecasting model to account for these potential challenges and ensure the accuracy of the forecasts (Akbulut and Demirci, 2019).

CONCLUSION

In conclusion, the figs production forecasting study conducted for Turkey spanning from 1961 to 2021, with projections up to 2031 using the ARIMA (0,1,3) model, offers significant insights for the figs industry and its stakeholders. Through the analysis of historical data, important trends, patterns, and seasonal variations in figs production were identified, contributing to a comprehensive understanding of its past dynamics.

The ARIMA (0,1,3) model was employed to generate forecasts by considering the observed historical patterns and seasonality in figs production data. These forecasts play a crucial role in facilitating decision-making, resource allocation, and strategic planning for farmers, policymakers, and other stakeholders.

The study's findings highlight the potential for growth in figs production in Turkey, providing guidance for farmers to optimize their cultivation practices and meet the projected market demand. Policymakers can utilize these forecasts to formulate targeted policies, support research and development initiatives, and foster the sustainability and competitiveness of the figs industry.

It is important to acknowledge that the accuracy of the forecasts is subject to uncertainties, including changes in climate, market conditions, and unforeseen events. Regular monitoring, evaluation, and refinement of the forecasting model are essential to ensure its reliability and accuracy over time.

Overall, this forecasting study offers valuable insights into the trends, seasonality, and potential future scenarios in figs production for Turkey. By leveraging these forecasts, stakeholders can make informed decisions, optimize resource allocation, and contribute to the growth and advancement of the figs industry in the country.

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