COMPARATIVE ANALYSIS OF TIME SERIES MODELS FOR FORECASTING RASPBERRY PRODUCTION IN SERBIA[1]

Dejana Vučković[2], Zoran Rajić[3], Marija Nikolić[4], Vladimir Zdravković[5]

Abstract

The aim of this paper is to model and forecast raspberry production in Serbia based on annual time series data for the period from 1970 to 2024. In the analysis, Exponential Smoothing models (Brown and Holt-Winters) and Autoregressive Integrated Moving Average models are applied, and compared to determine the most appropriate econometric model to describe and forecast the development of raspberry production in Serbia for the period from 2025 to 2030. The performance of the model was evaluated based on several criteria: Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error, both in-sample (2016-2020) and out-of-sample (2021-2024). Based on the observed prediction accuracy of the selected models, it can be concluded that the ARIMA model provides the best results for the prediction of raspberry production. According to the ARIMA model, a slight downward trend in raspberry production is expected from 2025 to 2030.

Key words: Forecasting, time series, ARIMA, exponential smoothing, raspberry production.

JEL[6]: Q11, C53, C22

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Introduction

Raspberry production in Serbia has a long-standing tradition, and is one of the most economically significant segments of fruit production. The economic importance of raspberry is evident in its strong competitive position, especially in the European Union market, where Serbian frozen raspberries are in high demand. This contributes not only to the country's foreign trade balance, but also to employment growth, overall income, and the development of the food industry.

The average raspberry production in Serbia from 2005 to 2024 was 95,931 tonnes, with the lowest production in 2012 (70,320 tonnes) and the highest in 2018 (127,010 tonnes). At the regional level, Šumadija and Western Serbia region had the highest production, averaging 84,152.6 tonnes during the observed period. Although the Vojvodina region is a relatively small producer compared to Šumadija and Western Serbia, it recorded the highest average annual growth rate of 7.73% (Table 1.).

Table 1. Dynamics of raspberry production by region in Serbia for the period 2005-2024.

Indicators	Arithmetic mean (tonnes)	Coefficient of variation (%)	Range of variation (tonnes)		Rate of change (%)	Share (%)
			Min	Max		
Republic of Serbia	95,931.1	17.49	70,320	127,010	0.61	100.0
Belgrade Region	1,985.8	73.25	414	5,051	1.15	2.07
Vojvodina Region	3,445.6	67.82	554	8,680	7.73	3.59
Šumadija and Western Serbia Region	84,152.6	14.71	63,604	104,894	0.32	87.72
Southern and Eastern Serbia Region	6,352.5	36.03	3,393	9,675	3.71	6.62

Source: Authors' calculations based on SORS, 2026.

According to the production level in 2024 (94.026 tonnes), Serbia was the second largest raspberry producer in Europe and the third largest in the world (FAO, 2025). Thanks to the quality of raspberries produced in Serbia, the country is the world's leading exporter of frozen raspberries, which accounted for about 25% of global exports in 2024 (within the total berries category – 081120), (ITC, 2025). In 2024, the export value of frozen raspberries from Serbia amounted to 312.7 million USD (ITC, 2025). Research by Nikolić et al. (2023) confirms that Serbia and Poland are world leaders in the frozen raspberry market, although Ukraine has seen a significant increase in competitiveness in recent years due to lower production costs. In contrast, fresh raspberries account for only a small share of Serbia's export structure.

Considering the importance of raspberry production for Serbia and the recent decline in production volume, the aim of this study is to forecast raspberry production for the period from 2025 to 2030. Forecasts serve as a basis for planning, as they provide information that enables the formulation of strategic decisions. Forecasting reduces uncertainties and risks, allows for a timely assessment of expected trends, and provides a basis for adopting appropriate agricultural policy measures. Continuous tracking, evaluation, and forecasting of agricultural production, together with an understanding of the key influencing factors, help ensure a reliable food supply and increase agri-food product exports. In addition, forecasting trends in agricultural production can help producers to choose production structures that ensure better economic outcomes (Ceranić, 2007). Raspberry production, like other agricultural crops, is characterised by low elasticity, which limits its ability to adapt quickly to market demand. In order to reduce market disruptions due to insufficient raspberry supply, it is necessary to make production forecasts and respond to future trends in a timely manner (Radosavljević, 2014).

In this study, Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing models were used to forecast raspberry production. A review of the literature shows that ARIMA and Exponential Smoothing models are widely used in agricultural production forecasting and demonstrate strong performance, especially for short-term predictions. Choudhury and Jones (2014) used ARIMA and Exponential Smoothing techniques to estimate crop yields in Ghana, highlighting their potential for analysing historical trends. Similarly, Dasyam et al. (2015) in India and Masood et al. (2018) in Pakistan compared ARIMA models and Exponential Smoothing methods for forecasting wheat production. Parreño (2023) demonstrated the use of these approaches in forecasting rice and maize production, emphasising that the Holt-Winters method offers superior predictive performance by effectively capturing underlying patterns and seasonality in agricultural data.

In the context of fruit production, Akin and Eyduran (2017) compared three ARIMA models (ARIMA (1,1,0), ARIMA (1,1,1), and ARIMA (0,1,1)) and three Exponential Smoothing models (Holt, Brown, and Damped) to forecast strawberry harvest area and production in Turkey. Kumari et al. (2022) applied ARIMA and Exponential Smoothing methods to forecast the area, production, and yield of citrus in Gujarat (India), finding that the ARIMA model performed better. In contrast, Ray et al. (2023) compared ARIMA and Exponential Smoothing models to forecast the production of multiple fruit crops in India, concluding that Exponential Smoothing models offer greater flexibility by capturing various trend and seasonal components, as well as the complex nonlinear structure of the data series.

Recent studies in this field have increasingly compared ARIMA and Exponential Smoothing models with machine learning approaches (Borrero, Borrero Domínguez, 2023; Ray et al., 2025; Khan et al., 2025).

Materials and Methods

Time series data on annual raspberry production for the period 1970-2024 were obtained from the database of the Statistical Office of the Republic of Serbia (SORS). The datasets were analysed using Microsoft Excel, SPSS, and the EViews software package, and the results were presented in both tabular and graphical formats.

This study compares Autoregressive Integrated Moving Average (ARIMA) models with Exponential Smoothing methods, Brown and the Holt-Winters Smoothing Method, to identify a suitable econometric model for capturing future trends in raspberry production for the period 2025 to 2030. The best-fitting model was selected using several fit criteria: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for both in-sample and out-of-sample forecasts. The period 2016 to 2020 was used to assess in-sample forecast accuracy, while the period 2021 to 2024 was used for out-of-sample comparison.

ARIMA

Time series modelling, developed by Box and Jenkins in 1976, combines three components - the Autoregressive (AR), Integrated (I), and Moving Average (MA) components into the ARIMA (p, d, q) model, which can be described by the following formula (Mladenović, Nojković, 2021):

$$\underbrace{\left(1-\phi_1 L-\phi_2 L^2-\cdots-\phi_p L^p\right)}_{\Phi(L)}(1-L)^d X_t=$$
$$\theta_0+\underbrace{\left(1-\theta_1 L-\theta_2 L^2-\cdots-\theta_q L^q\right)}_{\Theta(L)} e_t$$

Where:

p - the order of the autoregressive component;

d - the degree of differencing required for stationarity;

q - the order of the moving average component;

L - the time lag operator, $\mathrm{L}x_t = x_{t-1}$

Δ - first-order difference operator, $\Delta X_t = X_t - X_{t-1}$

$\phi_1, \phi_2 \dots \phi_p$ - autoregressive coefficients;

$\theta_1, \theta_2 \ldots \theta_q$ - moving average coefficients;

e_t - white noise.

The polynomials $\Phi(L)$ and $\Theta(L)$ are assumed to have no common factors and to represent, respectively, the autoregressive and moving average components of the stationary time series $(1-L)^d X_t$ (Mladenović, Nojković, 2021). The identification of an appropriate ARIMA model follows a systematic and iterative procedure comprising three main stages: model identification, parameter estimation, and model adequacy testing (Box et al., 2008). During the identification stage, the time series is examined for stationarity, trends, and seasonal patterns. If non-stationarity is detected, the series must be differenced to achieve stationarity. The autocorrelation and partial autocorrelation functions are then analysed to determine suitable orders for the autoregressive (p) and moving average (q) components. When several ARIMA (p, d, q) specifications are considered, model selection is based on standard information criteria, including the Akaike (AIC), Schwarz (SC), and Hannan-Quinn criteria (HQC).

The second phase of the Box-Jenkins methodology focuses on estimating the mean, variance, and model parameters. Ordinary least squares is used to estimate the parameters of the AR model, while nonlinear least squares is used to estimate the parameters of the MA and ARMA models (Box et al., 2008; Jovičić, Dragutinović Mitrović, 2011; Mladenović, Nojković, 2021).

During the model adequacy testing phase, residual analysis is conducted. For the selected model to be adequate, the residuals must be normally distributed and non-autocorrelated. The normality of the residuals is assessed using the Jarque-Bera test, while residual autocorrelation is examined using the Box-Pierce statistic or, for smaller samples, the modified version proposed by Box and Ljung (Gujarati, Porter, 2003; Mladenović, Nojković, 2021).

If the model is inadequate, its parameters must be re-estimated, followed by a new round of validation. This process is repeated until a satisfactory model is obtained, i.e. one that reliably represents the data and minimises forecasting errors. Successful completion of all three stages of the Box-Jenkins methodology ultimately enables the generation of accurate trend forecast for the variable under analysis within the specified time period.

Brown Exponential Smoothing

In addition to ARIMA modelling, double exponential smoothing methods are also applied in this paper. A negative bias may occur in forecasts when simple exponential smoothing is used on series with a trend. For this reason, that method was not used in the paper. To address this, exponential smoothing can be applied again to the result of simple exponential smoothing (Hansun, 2016; Mills, 2019). This procedure is called double exponential smoothing. The general expression for double exponential smoothing is the same as for simple exponential smoothing (Kovačić, 1995):

$$\mu_t = \alpha X_t + (1-\alpha)\mu_{t-1}$$

Then, with the series μ_t, the simple exponential smoothing procedure is repeated, using the expression for double smoothing (Kovačić, 1995):

$$\mu''_t = \alpha X_t + (1-\alpha)\mu''_{t-1}$$

In this way, the current value of the smoothed series (μ_t) represents a linear combination, that is, a weighted average of the current value of the time series (X_t) and the smoothed value from the previous period ($\mu_{t\text{-}1}$). The smoothing constant α, which ranges from 0 to 1, determines the weighting. However, with double exponential smoothing, the trend of the series is also directly updated using the equation (Kovačić, 1995):

$$T_t = \alpha(\mu_t - \mu_{t-1}) + (1-\alpha)T_{t-1}$$

Where, *Tt* is the trend component at time t. At the same time, future values are forecast using the following form (Kovačić, 1995):

$$\hat{X}_n(h) = \mu_t + \left(\frac{1-\alpha}{\alpha}\right)T_t + hT_t$$

Where, *h* denotes the forecast horizon.

Holt-Winters Exponential Smoothing

A disadvantage of the Brown model is that it uses the same smoothing constant for both, the level and the trend of the series. The Holt-Winter's model addresses this issue by allowing, but not requiring, the smoothing constants for level and trend to be equal (Winters, 1960; Kovačić, 1995; Dritsaki, Dritsaki, 2021).

In the Holt-Winters smoothing method, updating the trend and level of the series is based on two smoothing constants. The recursive form of the Holt-Winters model for a non-seasonal series is (Kovačić, 1995):

$$\mu_t = \alpha X_t + (1-\alpha)(\mu_{t-1} + T_{t-1})$$
$$T_t = \gamma(\mu_t - \mu_{t-1}) + (1-\gamma)T_{t-1}$$
$$\hat{X}_n(h) = \mu_t + hT_t$$

Evaluating the models

The selection of the most appropriate model for forecasting raspberry production in Serbia is based on RMSE, MAE, and MAPE values, calculated for both in-sample and out-of-sample forecasts. The preferred model is the one with the lowest forecasting errors, as these indicators measure the deviations between observed and predicted values.

$$RMSE = \sqrt{\frac{1}{T}\sum_{n=1}^{T}(x_{n+h} - \hat{x}_{n+h})^2}$$

$$MAE = \frac{1}{T}\sum_{n=1}^{T}|x_{n+h} - \hat{x}_{n+h}|$$

$$MAPE = \frac{100}{T}\sum_{n=1}^{T}\left|\frac{x_{n+h} - \hat{x}_{n+h}}{x_{n+h}}\right|$$

Where, *n* is the time period, *T* is the total number of observations, x_{n+h} is the actual value, and $\hat{x}_{n+h}$ is the forecasted value.

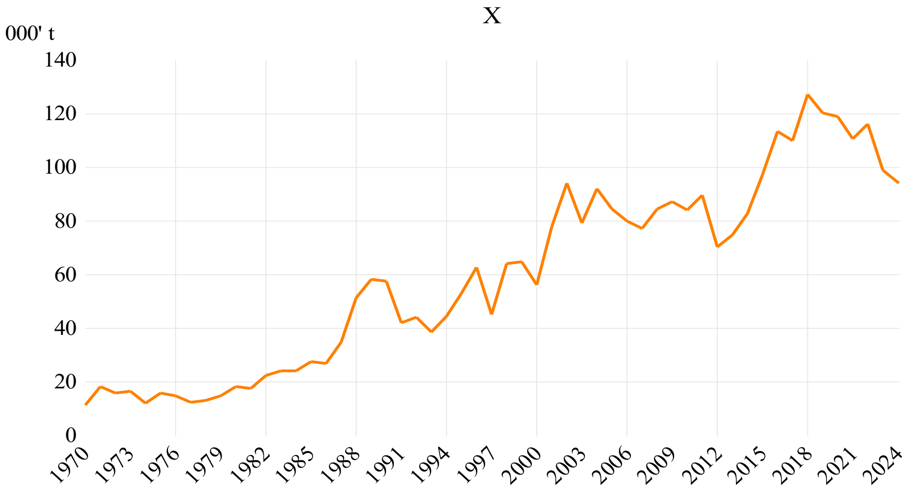
However, it should be emphasised that the choice of the "best" method depends on how the "best" is defined and the context in which it is applied. A method that produces good results for one phenomenon is not necessarily valid in another case. In the literature, the "best" is often equated with the most precise forecast within a given time period, while other aspects are often neglected (Lipovina Božović, 2014). Nevertheless, forecast accuracy is a criterion that can be considered from a statistical perspective, as is the case in this paper.

Results and Discussion

The analysed time series covers raspberry production from 1970 to 2024, with the period from 2021 to 2024 used for out-of-sample comparison. A visual review of the time series for raspberry production shows an increasing trend (Figure 1.). Although the series displays an overall upward trend, each period of raspberry production in Serbia has specific characteristics (Kljajić, 2014).

Raspberries were mainly grown extensively in Serbia during 1971-1980, resulting in production that remains around 15,044.7 tonnes, with no significant changes. However, from 1981 to 1990, raspberry production increased markedly, with the average production during this period reaching twice that of the previous decade, or 34,341.1 tonnes. This rapid growth was the result of a series of interconnected factors (Kljajić, 2014). Increased demand in the international market, driven by the quality of domestic raspberries compared to competing producers, played a key role. The introduction of new varieties and improvements in cultivation technology also contributed to higher productivity and efficiency. The modernisation of existing cold storages, along with the construction of new storage facilities, enabled better preservation of fruit quality and greater competitiveness in the market.

Figure 1. Production of raspberry in Serbia (1970-2024)



Source: Author's calculations using EViews software.

Raspberry production in 1991-2000 showed pronounced fluctuations, mainly due to low purchase prices at the start of the period, high production costs caused by inflation, and unfavourable weather conditions, especially after 1993 (Kljajić, 2014). However, since 1996, raspberry production has recovered significantly and increased.

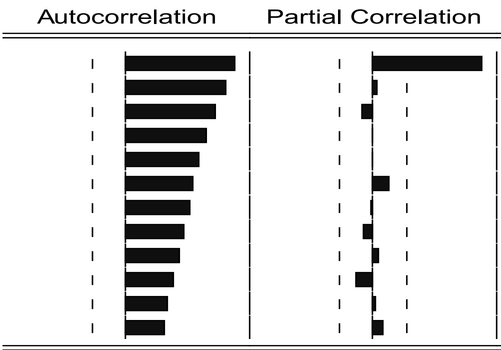
Between 2001 and 2010, raspberry production has remained relatively stable, with slight growth and no significant deviations. From 2011 to 2015, the growth trend in raspberry production continued, with some interruptions mainly due to unfavourable climatic conditions and the time required for new raspberry seedlings to reach full yield after the destruction of existing plantations (Radosavljević, 2014). A significant drop in production occurred in 2012 due to a severe drought, after which the growth trend in raspberry production resumed.

During the period from 2016 to 2024, 2018 stands out with a production level of 127,010 tonnes, the highest raspberry output recorded in the observed data series. However, since 2018, raspberry production has decreased each year, most likely due to the combined effects of climate change, market shocks, labour shortages, and reduced producer motivation (Kljajić, 2025). Additionally, the economic crisis during this period in countries that traditionally import raspberries from Serbia has led consumers to substitute expensive raspberries with cheaper fruits and other foods (Milošević et al., 2025).

Estimation of ARIMA model

To determine whether the trend in the time series of raspberry production from 1970 to 2020 is deterministic or stochastic, and to identify the stationarity properties of this time series, the ACF and PACF were first analysed. Estimates of these functions for the original raspberry production time series also indicate that the trend is stochastic. The values of the ordinary autocorrelation coefficients decrease slowly, while the partial autocorrelation coefficient is significant only at the first lag (Figure 2.), indicating the presence of a unit root.

Figure 2. Correlogram of ACF and PACF of raspberry production



	AC	PAC	Q-Stat	Prob
1	0.912	0.912	44.928	0.000
2	0.838	0.038	83.623	0.000
3	0.753	-0.097	115.54	0.000
4	0.679	0.005	142.02	0.000
5	0.610	0.001	163.88	0.000
6	0.572	0.140	183.53	0.000
7	0.533	-0.008	200.99	0.000
8	0.489	-0.075	216.02	0.000
9	0.457	0.053	229.46	0.000
10	0.401	-0.139	240.08	0.000
11	0.355	0.023	248.62	0.000
12	0.324	0.084	255.88	0.000

Source: Author's calculations using EViews software

To ensure reliable conclusions regarding stationarity, unit root tests were applied. Specifically, the Dickey-Fuller (DF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were used. The Dickey-Fuller test indicated that the series is non-stationary, and contains a single unit root. The KPSS test produced the same result.

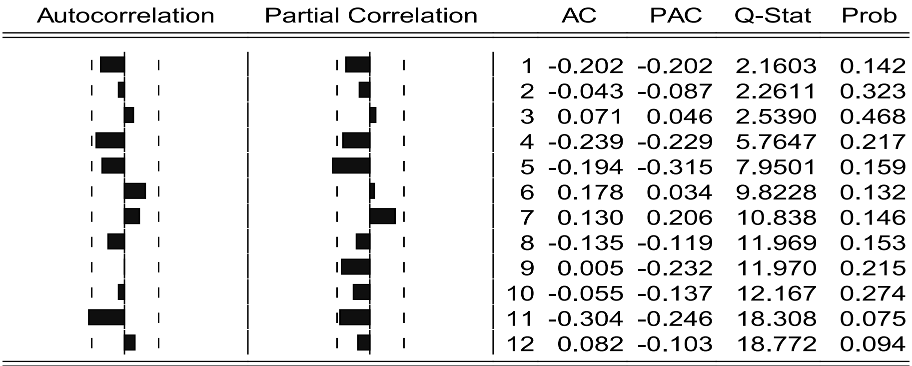
Table 2. Results of DF and KPSS test

Test	Statistic	Critical values at			Prob.	Decision
		1%	5%	10%		
DF at level	-0.50	-3.57	-2.92	-2.60	0.881	Non-Stationary
ADF (4) at first difference	-8.43	-3.57	-2.92	-2.60	0.009	Stationary
KPSS at level	0.93	0.74	0.46	0.35	0.000	Non-Stationary
KPSS at first difference	0.06	0.74	0.46	0.35	0.104	Stationary

Source: Author's calculations using EViews software.

Applying the first-difference operator results in a stationary time series, so the correlogram of the ACF and PACF for the first-differenced raspberry production data is used to determine the ARIMA model components (Figure 3.). As outlined in the methodology, the ARIMA (p, d, q) framework consists of an autoregressive component of order p, a differencing component of order d, and a moving average component of order q. The estimated specification includes an AR (1) component and MA components at lags 4 and 5, indicating p = 1 and q = 5, based on the highest significant MA lag. As the series exhibited a unit root, first-order differencing (d = 1) was applied to achieve stationarity. Therefore, the selected model is a reduced ARIMA (1, 1, 5), which has lower values for the information criteria (AIC, SC, and HQC), as well as a smaller standard error of regression than the other models considered.

Figure 3. Correlogram of ACF and PACF for first-differenced raspberry production series



	AC	PAC	Q-Stat	Prob
1	-0.202	-0.202	2.1603	0.142
2	-0.043	-0.087	2.2611	0.323
3	0.071	0.046	2.5390	0.468
4	-0.239	-0.229	5.7647	0.217
5	-0.194	-0.315	7.9501	0.159
6	0.178	0.034	9.8228	0.132
7	0.130	0.206	10.838	0.146
8	-0.135	-0.119	11.969	0.153
9	0.005	-0.232	11.970	0.215
10	-0.055	-0.137	12.167	0.274
11	-0.304	-0.246	18.308	0.075
12	0.082	-0.103	18.772	0.094

Source: Author's calculations using EViews software.

All components of the model are statistically significant. However, to assess the adequacy of the model, one must analyse the residuals. According to the Ljung-Box Q-test for autocorrelation and the Jarque-Bera JB-test for normality, the residuals are not autocorrelated and follow a normal distribution (Table 3.).

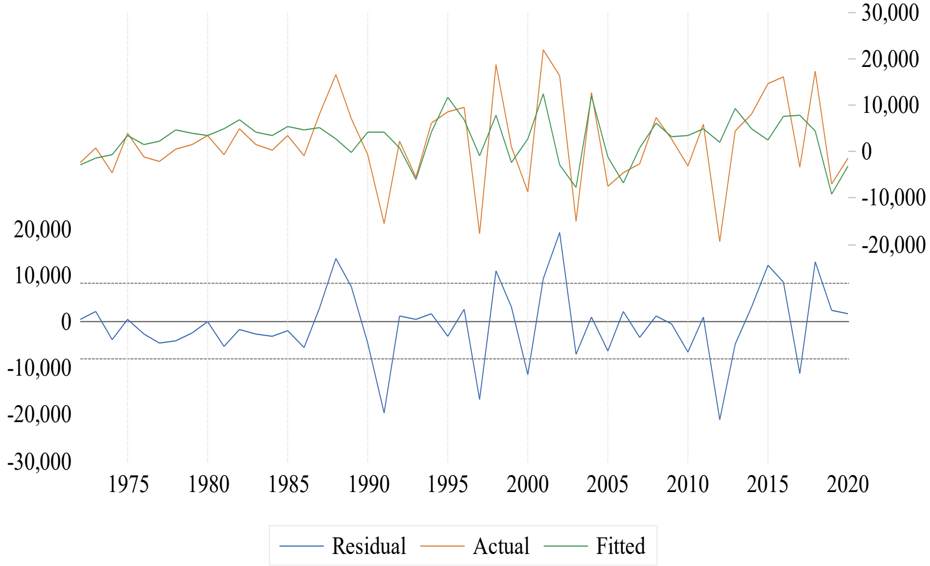
Table 3. Estimate of the level of raspberry production

Variable	Coefficient	t – statistic
Constant	2,272.9	7.18
AR(1)	-0.3271	-2.32
MA(4)	-0.4557	-3.60
MA(5)	-0.3723	-2.93
Q(12)=10.01 (0.35) JB=1.98 (0.37) AIC=20.9238 SC=21.0783 HQC=20.9824		

Source: Author's calculations using EViews software.

The choice of the ARIMA (1,1,5) specification also indicates a relatively high degree of agreement between the observed and model-estimated data (Figure 4.).

Figure 4. Actual and fitted values for first-differenced raspberry production



Source: Author's calculations using EViews software.

As the reduced ARIMA (1,1,5) model was found to meet all required properties, it was used to forecast raspberry production both within and outside the sample. The predicted values will be compared with the actual values and those obtained using the Brown and Holt-Winters methods.

Estimation of Brown Exponential Smoothing

When applying the Brown Smoothing Method, both the smoothing parameter and the initial value must be determined. In the literature, the smoothing constant is usually selected by testing different values and choosing the one that optimises the chosen statistical criterion, most often MSE of the forecast. When determining the starting value in Brown Exponential Smoothing, several methods can be used: the first observation or zero, the mean value of the series, splitting the series into two parts, the back-casting method, and the weighted least squares method, particularly for short time series (Kovačić, 1995).

In this paper, the Brown Smoothing Method was applied using the statistical programme SPSS, which determined a smoothing constant of 0.361 (Table 4.) and a starting value of 15,252 tonnes.

Table 4. Smoothing constant in Brown method

Parameter	Estimation	t statistic	Prob.
A	0.361	6.626	0.000

Source: Author's calculations using SPSS software

Estimation of Holt Winters Exponential Smoothing

In the Holt-Winters Method, different smoothing constants are applied to the level and trend components, which is the main difference compared to other smoothing methods. The evaluation of the smoothing constants and the starting value, as with Brown Smoothing Method, was performed using the SPSS statistical programme. The smoothing constant for the series level is 0.800, while the smoothing constant for the trend is 0.000 (Table 5.), and the estimated starting value of the forecast is 12,069 tonnes.

Table 5. Smoothing constants in Holt Winters method

Parameter	Estimation	t statistic	Prob.
A	0.800	5.590	0.000
Γ	0.000	0.001	0.999

Source: Author's calculations using SPSS software.

Model comparison

After applying three models to the time series of raspberry production (1970-2020), and generating in-sample forecasts (2016-2020), and out-of-sample forecasts (2021-2024), comparative analysis of the predictions was conducted. Based on this analysis, the model that gives the best forecasts for raspberry production is determined. For the comparative analysis, the values of RMSE, MAE, and MAPE for both within-sample and out-of-sample forecasts were used.

Based on the calculated in-sample accuracy measures, the ARIMA model exhibits the lowest values across all selected forecast error indicators (Table 6.). In contrast, according to the same criteria, the Brown Smoothing Method provides the weakest in-sample forecast performance for raspberry production.

When evaluating out-of-sample forecast performance, the ARIMA model again achieves the lowest MAE and MAPE values. According to these indicators, the Holt-Winters Smoothing Method ranks the second in forecast quality, while consistent with the in-sample results, the poorest forecast of raspberry production is obtained using the Brown Smoothing Method.

Table 6. Evaluation of the in-sample and out-of-sample forecasts of the analysed models

Element	ARIMA	BMI	HWMI	ARIMA	BMI	HWMI
	in-sample 2016-2020			*out-of-sample 2021-2024*		
RMSE	7,262.4	12,601.5	10,516.3	16,924.3	31,130.4	23,069.9
MAE	7,055.1	10,630.6	8,892.0	12,767.5	37,720.1	20,268.8
MAPE (%)	5.95	8.99	7.49	13.16	28.22	20.36

Source: Author's calculations.

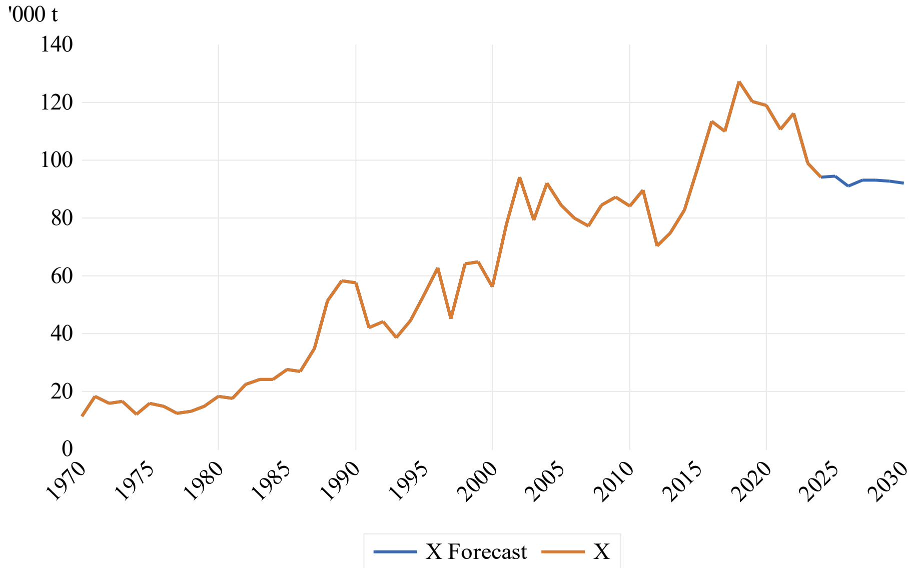
The results of the forecast performance of the selected models, both in-sample and out-of-sample, indicate that the ARIMA model provides the most accurate prediction of raspberry production. In practice, comparing forecast quality essentially involves testing the differences between predicted and actual out-of-sample values of the series (Lipovina Božović, 2014), so it is expected that the ARIMA model will achieve higher forecast accuracy over longer prediction horizons. Therefore, the reduced ARIMA (1,1,5) model was selected to forecast raspberry production for 2025-2030.

These results are consistent with the findings of Choudhury and Jones (2014), or Dasyam et al. (2015), Masood et al. (2018), and Kumari et al. (2022), who also demonstrated that the ARIMA model is more suitable for forecasting than exponential smoothing methods. However, some studies report the opposite, indicating that one of the double exponential smoothing methods achieves better forecasts than ARIMA modelling (Akin, Eyduran, 2017; Parreno, 2023; Ray et al., 2023).

Selecting the most appropriate forecasting method is complex, as no research has fully identified the decisive characteristics for selecting a particular forecasting method (Petropoulos et al., 2014). Consequently, the accuracy of each method has been evaluated in scientific papers (Da Veiga et al., 2014).

The ARIMA model predicts a slight downward trend in raspberry production for the period 2025 to 2030 (Figure 5.). The average raspberry production (2019-2024) was 109,686 tonnes, while the forecast for 2025 to 2030 indicates a lower average of 92,617 tonnes. Since 2020, a significant decrease in the area under raspberries has been observed, which is directly reflected in total production volume. This trend suggests declining interest among producers, possibly due to unstable purchase prices, increased production costs, and several market and climate challenges.

Figure 5. Forecast of future raspberry production in the period 2025-2030 in Serbia



Source: Author's calculations using EViews software

The projected decline in raspberry production can also be explained by several underlying economic factors. In recent years, producers have faced increasing production costs, particularly in labour, inputs, and energy, while purchase prices have shown significant volatility. This reduces profitability and increases production risk, leading to a gradual decline in producer interest. In addition, strong competition from other producing countries, especially those with lower production costs, additionally limits Serbia's price competitiveness in international markets. These economic pressures contribute to the observed downward trend in raspberry production. This also suggests that the decline in production is not driven solely by natural or technical constraints, but may also reflect an unfavourable position of primary producers within the value chain, where a significant share of value is captured in downstream segments such as processing and trade.

Although the ARIMA model provides the most accurate forecasts of raspberry production in this study, it has certain limitations, particularly in modelling non-linear relationships between variables (Siami Namini et al., 2018). Therefore, comparison and evaluation of forecasting methods and models remain necessary to further improve prediction accuracy in agriculture, especially given the sector's specific characteristics.

Conclusion

In this study, raspberry production forecasts were analysed using time series models. Data on annual production from 1970 to 2024 were used. The results showed that forecasts obtained with the ARIMA model, both in-sample and out-of-sample, were closer to actual values than those obtained using Brown and Holt-Winters Smoothing Methods.

For this reason, the selected ARIMA model was used to forecast raspberry production for the period 2025-2030. The research shows that the average production level during this period is expected to be lower than in the previous five years. To halt the decline in raspberry production and prevent a loss of competitiveness in the global market, it is necessary to restore producers' motivation through agricultural policy measures and modernise production processes to address key challenges, particularly climate change.

However, ARIMA models are not entirely precise and have limitations in time series modelling, especially in agricultural production, which largely depends on weather conditions. In addition, this study did not consider potential structural shocks arising from external factors. Therefore, future research should examine possible structural breaks in the raspberry production time series, as well as compare ARIMA models with artificial intelligence methods, which can incorporate more information to produce more accurate forecasts of agricultural production.

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