FORECASTING MAIZE PRODUCTION IN REPUBLIC OF SERBIA USING ARIMA MODEL

Dejana Vučković¹, Svjetlana Janković Šoja², Tamara Paunović³ *Corresponding author E-mail: vuckovicd@agrif.bg.ac.rs

ARTICLE INFO

ABSTRACT

Original Article Received: *01 February 2024* Accepted: *25 March 2024* doi:10.59267/ekoPolj24041129V UDC 635.67:519.246.8(497.11)

Keywords:

maize production, time series, ARIMA model, forecast, Republic of Serbia

JEL: Q16, M24

Considering the importance of maize in the Republic of Serbia, the aim of the paper is to select an appropriate econometric model that describes and predicts the future trends of maize production in the Republic of Serbia. In order to forecast the future trends of maize production from 2023 to 2027, a time series of annual data from 1990 to 2022 was analyzed using the autoregressive integrated moving average model. The model shows that maize production in 2023 will be 49.34% higher than in 2022. According to the forecast, the growth trend in maize production will continue until 2025, after which a decline in production is predicted. This paper also found that the autoregressive integrated moving average model for the selected time series of maize production provides approximate and more reliable forecast results than the extrapolation of the average annual rate of change.

Introduction

Agricultural production has multiple significance for the socio-economic development of the Republic of Serbia, which is reflected in food production, production of raw materials for other sectors of the economy, foreign trade and various social aspects. For this reason, in the Smart Specialisation Strategy of the Republic of Serbia for the period from 2020 to 2027, agriculture and food production are presented as one of the priority sectors, assuming that investments in the technological development of agriculture would improve the technological and economic development of Serbia (Semenčenko et al., 2021).

¹ Dejana Vučković, Assistant, Faculty of Agriculture, Belgrade University, Nemanjina Street no. 6, 11080 Zemun – Belgrade, Serbia, Phone: +381631881455, E-mail: vuckovicd@agrif. bg.ac.rs, ORCID ID (https://orcid.org/0000-0001-9365-8634)

² Svjetlana Janković Šoja, Associate Professor, Faculty of Agriculture, Belgrade University, Nemanjina Street no. 6, 11080 Zemun – Belgrade, Serbia, Phone: +381605549604, E-mail: svjetlanajs@agrif.bg.ac.rs, ORCID ID (https://orcid.org/0000-0002-5474-9039)

³ Tamara Paunović, Assistant Professor, Faculty of Agriculture, Belgrade University, Nemanjina Street no. 6, 11080 Zemun – Belgrade, Serbia, Phone: +381631064089, E-mail: tamara@agrif.bg.ac.rs, ORCID ID (https://orcid.org/0000-0003-4747-0678)

In Serbia, plant production has a dominant share in the structure of agricultural production (70%). Within plant production, field crop and vegetable production is the most represented and accounts for more than 50% of total plant production (Đoković et al, 2018). Since field crop production is the basis of all agriculture, the results achieved in this production have a significant impact on the overall balance of agricultural production (Munćan and Živković, 2014). Arable land in Serbia has traditionally been used to grow the most grain, with maize accounting for the largest share of both total arable land and total grain production.

In terms of area under cultivation and its importance for the economy of the Republic of Serbia, maize is the most important crop alongside wheat. In 2021, maize occupies the largest area of the total utilised arable land (1,770,188 ha) with an area of 1,020,337 ha (SORS, 2021). The second most common crop is wheat with an area of 598,735 ha. Due to their strategic importance and the favourable agro-ecological conditions for cultivation, wheat and maize together account for 91.46% of the total area, i.e. 92.51% of the total production of the grain.

Due to the expansion of the area under maize cultivation areas and the increase in average yields, global production of maize has grown at an annual growth rate of 3.45% over the last two decades, from 592 million tons in 2000 to 1,210 million tons in 2021 (FAO, 2021). The main factors contributing to the increase in maize production are: the development of technology and the seed industry, the increase in agrotechnical efficiency, innovations in the development of a wide range of food and technical products from maize and, in particular, innovations in the production of bioethanol and the increase in its use as an alternative fuel (Bekrić and Radosavljević, 2008).

The largest maize producer in the world is the United States of America with 31.70% of global production, followed by China with 22.58% and Brazil with 7.31% (FAO, 2021). Together, these countries account for more than half of global maize production, and it is characteristic of them that they have highly developed livestock farming, for which maize is a necessary raw material (Vlahović, 2015). Important world producers are Argentina, India, Mexico, Indonesia and South Africa, while the largest European producers are Ukraine and France. According to the 2021 ranking, Serbia ranks 20th in the world with a maize production of about 6 million tons (USDA, 2021), while it ranks 7th according to the ranking of producers in the European Union (Eurostat, 2021).

The importance of maize results from its use for human nutrition, for domestic animals and for industrial processing. The particular economic and commercial importance of maize results from the fact that almost all parts of the plant can be used for processing (Simić et al., 2008). Maize also occupies an important place in the structure of agricultural exports, where it is the most represented export product in Serbia next to raspberries. According to the realized export of corn in 2021, Serbia ranked 13th in the world, and 5th compared to the exporters of the European Union. The export of corn from Serbia amounts to 2.3 million tons, which corresponds to a value of about 600 million dollars.

Considering the fact that maize occupies a dominant place in the structure of the total arable land, that it is one of the most important export products of the Republic of Serbia, as well as its importance for immediate nutrition and the processing industry, the aim of the paper is the analysis of time series, as well as the selection of an appropriate econometric model with which the future trends of maize production in the Republic of Serbia can be described and predicted.

Forecasts are the basis of planning because they provide information that enables planning decisions to be made. In this way, forecasting aims to reduce uncertainty and risk in the future. The importance of forecasts in agriculture is reflected in the adoption of agricultural policy measures designed to mitigate negative trends and steer the development of the agricultural sector in the desired direction. Monitoring, analyzing and forecasting data on agricultural production and considering the factors that influence it can help ensure stable food production and increase food exports. In addition, predicting trends in agricultural production can help producers choose a production structure that can achieve the best economic results.

In order to obtain information about possible trends in the future, it is necessary to examine data from the past and the present. For this reason, in order to predict future trends in maize production in the Republic of Serbia from 2023 to 2027, a time series of annual data from 1990 to 2022 was analyzed using ARIMA modeling. Although various quantitative methods and models can be used for prediction, ARIMA modeling is used in this paper because it is the predominant statistical method in predictions based on regression analysis, especially when analyzing phenomena whose current value is largely determined by past values (Wihartiko et al., 2021).

The choice of the most appropriate forecasting method is a very complex task, as no study has conclusively correlated the characteristics that determine the choice of a particular forecasting method (Petropoulos et al., 2014). For this reason, the accuracy of each method has been tested in scientific studies (Da Veiga et al., 2014). Ahmad et al. (2017) point out that ARIMA as a univariate model has several advantages over its multivariate alternatives, namely suitability also for non-stationary time series, statistical strength for reliable forecasts from small data sets and requirement of data only for the time series to be forecast, but not for its determinants. Jadhav et al. (2017) emphasize that the strength of the ARIMA model lies in the fact that the method is suitable for any time series with any pattern of change and the forecaster does not have to choose a priori values for a parameter. Dasyam et al. (2015) found that the ARIMA model is better suited for forecasting the development of wheat production in India than Parametric regression and Exponential smoothing models. Choudhury & Jones (2014) compared the prediction of maize yields using different models such as Simple Exponential Smoothing, Double Exponential Smoothing, Damped-Trend Linear Exponential Smoothing and ARMA and found that the ARMA model is preferable to the other models. When forecasting rice production in Bangladesh, Hamjah (2014) found that the ARIMA model also performs well for forecasts based on short-term time series. In fact, there are a large number of scientific papers that justify the choice of the ARIMA model when forecasting future trends in agriculture based on time series data.

http://ea.bg.ac.rs

In the Republic of Serbia, Dokovic et al. (2019) predicted maize yields in 2017 and 2018 using the ARIMA model and concluded that the time series model cannot predict exact yield quantities, but that it is useful for predicting future trends in maize yields. Based on the ARIMA (1,1,1,2) model chosen to predict maize production from 2015 to 2017, Ilić et al. (2016) found a stagnation of the trend over the years and predicted a decrease in total maize production in the Republic of Serbia by about 20% from 2015 to 2017. In addition to predicting the future trends of area, yield and production of maize, the authors also predicted the future trends of these production indicators of other agricultural crops. By analyzing time series using ARIMA modeling, Mutavdžić and Novković (2016) predicted the production parameters of cabbage in the Republic of Serbia for the period from 2015 to 2020, and Novković et al. (2010) predicted the production of the three most common vegetable crops in Vojvodina - potatoes, beans and tomatoes - for the period from 2006 to 2010.

Changes in the price of agricultural products have an impact on farmers' incomes and food security. For this reason, many authors have predicted the future changes in agricultural prices and their parities. In the Republic of Serbia, the authors mainly use the ARIMA model to forecast the prices of agricultural products. Novković et al. (2019) predicted the development of wheat and maize prices in the period from 2018 to 2022, while Mutavdžič et al. (2016) predicted the development of maize-wheat price parity and deflated wheat and maize prices from 2015 to 2020. Ivanišević et al. (2015) analyzed the changes and predicted the future development of the tomato price from 2011 to 2015 with the aim of forecasting the real, absolute and relative (parity with wheat) price of tomatoes, i.e. predicting the economic conditions for production.

The alleged importance of maize is not only in our country but also at the global level, which is why many authors in the world have dealt with the prediction of maize production using various methods. Yadav et al (2022) forecast maize production in South Asian countries using state space models and ARIMA models, where the research results show that there is a trend of increasing maize production in all selected South Asian countries from 2020 to 2027. Based on the application of the ARIMA model, Suleman & Sarpong (2012) predicted an increasing trend in the production and consumption of maize in Ghana from 2012 to 2021, while Badmus & Ariyo (2011) predicted an increase in maize area and production in Nigeria from 2006 to 2020.

However, it should be borne in mind that absolute reliability of forecasts cannot be guaranteed, especially when it comes to agriculture. The limits of forecasting agricultural production result from its particular characteristics, which are mainly:

- the dependence of overall agricultural production on natural factors;

- the instability of markets and prices;

- a lengthy production process and the impossibility of changing production in the short term.

Materials and methods

The database of the Statistical Office of the Republic of Serbia (SORS), but also the statistical databases of the United Nations (UN Comtrade Database and USDA) and the Food and Agriculture Organization (FAOstat) were used for the preparation of this paper. The collected data was analyzed using the EViews software package.

Statistical methods of one-dimensional analysis of time series were applied in the data analysis, i.e. the Box-Jenkins modeling strategy. The Box-Jenkins modeling strategy is applied to select the appropriate model that describes the movement of the data set of the selected time series - maize production from 1990 to 2022 (annual data) - and predicts future values.

In 1976, Box and Jenkins proposed a strategy for modeling time series that consists of three phases:

- 1. model identification;
- 2. estimation of model parameters; and
- 3. verification of model adequacy.

The model identification phase involves the selection of a narrow class of ARIMA models that can be considered as generators for a given data set. However, in order to perform the model selection, it must first be determined whether the time series is stationary, since this modeling strategy assumes that the time series is stationary. The stationarity of the time series is examined with the help of a graphical representation of the given series, the ordinary and partial autocorrelation functions and the unit root tests. If the time series is not stationary, it must be transformed in order to obtain a time series that has a symmetrical and normal distribution as well as a stable level and stable variability. To achieve a symmetric and normal distribution, the Box-Cox transformation is most commonly used, which is reduced to the logarithmization of the initial data, while to stabilize the level of the time series, the transformation is performed by differentiating the data (Mladenović and Nojković, 2021).

When choosing a model, it is necessary to aim for the number of AR and MA components in the model to be optimal, that is, to choose the simplest ARIMA model that well explains the movement of the time series. Information criteria are used for this purpose: Akaike Information Criterion (AIC), Schwartz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQC), whereby the model with the lowest value of these criteria is selected.

In the next phase of the Box-Jenkins methodology, the model parameters identified in the previous phase are evaluated, that is, the mean value, variance and coefficients in the model are evaluated. The method of ordinary least squares is used to estimate the parameters of the AR model, while the method of nonlinear least squares is used to estimate the parameters of the MA and ARMA models (Mladenović and Nojković, 2021).

Checking the adequacy of the model, within the third phase of the Box-Jenkins methodology, involves checking the residuals, that is, the difference between the actual values and those predicted by the model. In order for the model to be considered adequate, it is necessary that the residuals are normally distributed and not autocorrelated, whereby the Jarque–Bera test is used to test the hypothesis that the residuals are normally distributed, while the Box-Pierce statistic is used to test the hypothesis that there is no autocorrelation in the residuals, that is, for smaller samples, corrected Box-Pierce statistics, whose authors are Box and Ljung.

If it turns out that the selected model is suitable, it can be used to predict the future development of the time series. Within the Box-Jenkinson method, the backward prediction method is used, which is based on the reversal of the temporal sequence by starting the evaluation procedure from the last to the first observation (Kovačić, 1995).

If, in the third phase of the Box-Jenkinson method, it is determined that the model is not appropriate, one must return to the model identification phase and try to find a better model. This leads to the conclusion that the Box-Jenkins modeling strategy is an iterative process that ends when a suitable model has been found in accordance with the general principles of modeling.

Results

Time series analysis is the subject of research in various scientific fields such as meteorology, demography, economics, medicine and agriculture. In this paper, the time series in agriculture was analyzed, i.e. the development of maize production was observed.

The aim of the graphical representation of a time series is to visually inspect it in order to determine whether the series shows a trend, a seasonal variation, a structural break or an unstable variance. The time series presented covers the values of maize production from 1947 to 2022, with a total number of observations of 76 (*Figure 1*). The data are given in tons. A visual inspection of the initial series suggests that the series showed a clear upward trend until the 1980s, while a slight upward trend can be observed from the early 1990s onwards. Similar observations were made in other studies (Đoković et al., 2019; Ilić et al., 2016), whereby it is assumed that a break in the structure of the time series took place in the 1980s. For this reason, the time series of maize production in the period from 1990 to 2022 is analyzed in this paper.

In the period from 1980 to 1990, there was a significant consumption of mineral fertilizers in Serbia, with the highest consumption recorded in 1986 (Bogdanović, 2010), which had an impact on the volume of maize production, which peaked at 8,062,020 tons. The uncontrolled use of mineral fertilizers was soon abolished by the introduction of the system for controlling soil fertility and fertilizer use as a control system of plant production factors, which significantly reduced the consumption of mineral fertilizers.



Figure 1. Maize production in the period 1947-2022, in the Republic of Serbia (t)

Source: Created by the author based on data analysis in EViews

In the period from 1947 to 1990, the average area under maize cultivation was 1,329,348 ha, while the average yield was 3.25 t/ha. In the second observation period, from 1990 to 2022, the average area under maize cultivation was 1,116,558 ha and the average maize yield was 5.20 t/ha. Although the area under maize declined from 1990 to 2022, the average yield increased (especially since 2005), resulting in a higher average production volume during this period. The increase in maize yields is the result of constant progress in breeding and the creation of more fertile hybrids, but also the improvement of cultivation methods under the influence of the development of the agricultural machinery industry, the mineral fertilizer and pesticide industry (Starčević and Latković, 2006). However, since in the period after the 1990s significant climatic disturbances occurred worldwide, which also affected the territory of the Republic of Serbia, the volume of maize production is characterized by fluctuations from year to year due to unfavorable weather conditions (droughts, floods, etc.).

The time series in the period from 1990 to 2022 with 33 observed values oscillates around a mean value that is not zero (*Figure 2*). It is a stationary series, which is confirmed by the analysis of the ordinary and partial autocorrelation functions and the results of the unit root test.



Figure 2. Maize production in the period 1990-2022, in the Republic of Serbia (t)

Source: Created by the author based on data analysis in EViews

When analyzing a time series, it is necessary to look at its correlation structure, which is a schieved with the help of the autocorrelation function, which is a series of autocorrelation coefficients with respect to time. Autocorrelation coefficients are statistically significant at the 95% significance level if their estimated value is outside the interval [-0.341, 0.341]. Since the assessment of the ordinary autocorrelation coefficients for the first ten lags is within the interval (*Table 1*), the null hypothesis that there is no significant autocorrelation coefficients for the analyzed maize production time series are also within the confidence interval, it is concluded that they are not statistically significant for any of the observed lags. The estimation of the ordinary and partial autocorrelation function indicates the stationary nature of the series.

 Table 1. The sample and partial autocorrelation functions for the annual maize production series in the period 1990-2022

lags	1	2	3	4	5	6	7	8	9	10
AC	-0,071	-0,054	-0,069	0,111	0,250	0,092	-0,079	-0,024	0,050	0,247
PAC	-0,071	-0,059	-0,078	0,098	0,263	0,157	-0,014	-0,007	-0,007	0,169

Source: Created by the author based on data analysis in EViews

In order to obtain reliable conclusions about the stationarity of the series, unit root tests must be carried out. To test for the presence of a unit root in the maize production time series, the Dickey-Fuller test was applied using the τ_{μ} statistic.

Therefore, the null hypothesis that the time series of maize production has at least one unit root $(H_0: \varphi = 0)$ was compared with the alternative hypothesis that the

time series of maize production is stationary around a non-zero mean $(H_1: \varphi < 0)$. The least squares method was used to evaluate the parameters of the model $\Delta X_t = \beta_0 + \varphi X_{t-1} + e_t$ and the value of the DF test statistic was determined: $\tau_{\mu} = -6,08 \ (\tau_{\mu} = \hat{\varphi} / \mathbf{s}(\hat{\varphi})).$

Since the calculated value of the DF τ_{μ} test statistic is below the critical value -2,96⁴ (-6,08 < -2,96), the null hypothesis of the existence of a unit root is rejected and it is concluded that the time series of maize production from 1990 to 2022 is stationary around a non-zero mean value.

Once the time series is determined to be stationary, the next step in the Box-Jenkins approach is to determine the autoregressive (p) and moving average components of the model (q). The determination of the value of p and q is based on the analysis of the sample and partial autocorrelation function of the series transformed as a function of the number of roots, where the order of the autoregressive component (p) is determined based on the partial autocorrelation function, while the order of the moving average component is determined based on the sample autocorrelation function (q).

In order to find the best possible model, several models with different combinations of AR and MA components were examined in the study of the maize production time series, and it was found that the optimal model is the reduced ARMA(5,1). First, it was found that both components of the model, AR(5) and MA(1), were statistically significant and had lower values of the information criteria (AIC, SC, HQC) and regression standard errors compared to other models, which is why this model was chosen for predicting future values (*Table 2*).

For the model to be considered appropriate, it must fit the data, which is checked using a series of residuals. The residuals must not be autocorrelated and must be normally distributed. The presence of an autocorrelation of the residuals on all lags up to K was tested using the Box-Ljung Q test statistic and the corresponding p-value. At a significance level of 5%, it is determined that there is no autocorrelation in the series of residuals Q(10)=2.78 (p=0.95). The normality of the residuals was tested with the Jarque-Bera (JB) test statistic. The calculated value of the JB test statistic is 0.32, which is below the critical value, which is about 4.74 for this sample size at a significance level of 5% (Patterson, 2000 in Mladenović and Nojković, 2021), which is why it is concluded that the distribution of the residual series of maize production is normal.

http://ea.bg.ac.rs

⁴ The critical value at the significance level of 5 % is calculated using the following formula: $\tau_{\mu}^{k} = -2,8621 - \frac{2,738}{T} - \frac{8,36}{T^{2}}.$

Variable	Coefficient	t – statistic				
Constant	6147693	18,13				
AR(5)	0,4823	2,71				
MA(1)	-0,4267	-2,31				
Q(10)=2,78 (0,95) JB=0,32 (0,85) AIC=31,0147 SC=31,1575 HQC=31,0584						

 Table 2. Estimate of the level of annual maize production in the period 1990-2022

Source: Created by the author based on data analysis in EViews

The selected specification of the reduced model ARMA (5,1) describes the correlation structure of the data relatively accurately, i.e. the degree of agreement between the actual and the model-predicted values of the ordinary and partial autocorrelation coefficients (*Figure 3*).

Figure 3. Estimated and model-predicted value of the sample and partial autocorrelation function in the time series of maize production in the period 1990-2022



Source: Created by the author based on data analysis in EViews

Based on the selected ARMA(5,1) model, the development of maize production is predicted from 2023 to 2027. A comparison of the maize production predicted by the model (5,000,686 tons) and the actual production (4,523,043 tons) in 2022 shows that the model prediction indicates a decline, which is, however, slightly lower than the actual production. The weather conditions, particularly the high temperatures and lack of precipitation contributed to a significant decline in maize production in 2022.

Compared to maize production in 2022 (4.52 million tons), maize production in 2023 will be 49.34% (6.75 million tons) higher, as the results show. The forecast maize production has an upward trend until 2025, after which a decline in production is predicted (Figure 4). Compared to the average maize production (6.34 million tons) of the last ten years (2013 to 2022), the average of the forecast maize production values for the period from 2023 to 2027 (6.38 million tons) remains roughly the same.

Although Serbia has favorable conditions for maize cultivation, in some years there are periods of drought or excessive rainfall, which leads to a decline in production and the quality of maize grains. To mitigate the effects of climate change on maize production, the most important adaptation measures are earlier sowing, the introduction of irrigation and the selection of tolerant hybrids (Bekavac, 2010).



Figure 4. Forecast of future maize production in the period 2023-2027 in the Republic of Serbia

Source: Created by the author based on data analysis in EViews

To confirm the appropriateness of the chosen ARIMA model, the prediction of the development of maize production for the year 2022 was also carried out using the average annual rate of change used in the work of Novković et al. (2022) for the prediction of maize production parameters from 2021 to 2023. The year 2022 was chosen because the Statistical Office of the Republic of Serbia has published data on actual maize production, which allows a comparison of the predicted production with the actual production.

Based on the time series of data from 1990 to 2021, extrapolation of the average annual rate of change results in a projected maize production of 6,134,315 tons in 2022. The predicted value is not only not close to the actual production, but also indicates an opposite trend in maize production in 2022 compared to the previous period. The difference between the maize production predicted by the ARIMA model and the actual maize production in 2022 is about 10%, while the difference between the predicted maize production using the average annual rate of change and the actual maize production using the average annual rate of change and the actual maize production is about 26%. This confirms that the selected ARIMA model is more reliable for predicting future values in the used time series of maize production from 1990 to 2021 than the extrapolation of the average annual rate of change.

However, it should be noted that even ARIMA models are not completely accurate and have their limitations when modeling time series. The limitations of ARIMA models

http://ea.bg.ac.rs

are that it is difficult to model non-linear relationships between variables and the assumption that there is a constant standard deviation in errors in these models (Siami-Namini et al., 2018).

In order to achieve the greatest possible accuracy in predicting future trends in agriculture, it is necessary to continuously research methods and models that can be used for this purpose. As the importance of using artificial intelligence methods for predicting future trends in agriculture, especially methods based on neural networks, is increasingly emphasised, their application and comparison with ARIMA models should be the subject of future research.

Conclusions

The Republic of Serbia is an important maize producer in Europe and the world. For this reason, the time series of maize production in the Republic of Serbia from 1990 to 2022 was analyzed. In order to analyze the mentioned time series and to find a suitable econometric model that can predict the trends of future values, the Box-Jenkins modeling strategy was applied.

Regarding the time series of maize production from 1990 to 2022, the model with satisfactory properties is the reduced ARMA(5,1), which is used to predict future trends in maize production from 2023 to 2027. The year 2022 is also included in the forecast to allow a comparison between the maize production predicted by the model and the actual maize production. Comparing the maize production predicted by the model (5,000,686 tons) with the actual maize production (4,523,043 tons) in 2022 shows that the model prediction shows a decrease, but slightly below the actual production. According to the forecast values, maize production in 2023 will be 49.34% higher than in 2022. The growth trend in maize production is likely to continue until 2025, after which production is expected to decline. In order to increase maize production in the future, production techniques must be adapted to climatic conditions, appropriate land reclamation and conservation measures and other environmental factors.

Although it was found in this paper that the ARIMA model provides more accurate and reliable prediction results for the selected time series of corn production from 1990 to 2021 than the extrapolation of the average annual rate of change, the ARIMA model also has its limitations and cannot predict completely accurate data. For this reason, it is necessary to continuously compare methods and models to further improve the accuracy of predictions in agriculture.

Acknowledgements

The article is part of the research work carried out within the framework of the contract for the implementation and financing of scientific research work in 2024 between the Faculty of Agriculture in Belgrade and the Ministry of Education of the Republic of Serbia, contract number: 451-03-65/2024-03/200116.

Conflict of interests

The authors declare no conflict of interest.

References

- Adisa, O. M., Botai, J. O., Adeola, A. M., Hassen, A., Botai, C. M., Darkey, D., & Tesfamariam, E. (2019). Application of artificial neural network for predicting maize production in South Africa. *Sustainability*, *11*(4), 1145. doi.org/10.3390/ su11041145
- 2. Ahmad, D., Chani, M. I., & Humayon, A. A. (2017). Major crops forecasting area, production and yield evidence from agriculture sector of Pakistan. *Sarhad Journal of Agriculture*, *33*(3), 385-396. doi: 10.17582/journal.sja/2017/33.3.385.396
- 3. Badmus, M. A., & Ariyo, O. S. (2011). Forecasting cultivated areas and production of maize in Nigerian using ARIMA Model. *Asian Journal of Agricultural Sciences*, *3*(3), 171-176.
- 4. Bekavac, G., Purar, B., Jocković, D., Stojaković, M., Ivanović, M., Malidža, G., & Dalović, I. (2010). Maize Production in Terms of Global Climate Changes. *Field & Vegetable Crops Research*, *47*(2), 443-450.
- 5. Bekrić, V., & Radosavljević, M. (2008). Contemporary approaches to maize utilization. *Journal on Processing and Energy in Agriculture*, 12(3), 93-96.
- 6. Bogdanović, D. (2010). Fertilizers consumption in our country since the beginning of chemical inputs use in agriculture up to now. *Yearbook of the Faculty of Agriculture Novi Sad*, 34(1), 32-45.
- 7. Choudhury, A., & Jones, J. (2014). Crop Yield Prediction Using Time Series Models. *Journal of Economics and Economic Education Research*, 15(3), 53-67.
- 8. Da Veiga, C. P., Da Veiga, C. R. P., Catapan, A., Tortato, U., & Da Silva, W. V. (2014). Demand forecasting in food retail: A comparison between the Holt-Winters and ARIMA models. *WSEAS transactions on business and economics*, *11*(1), 608-614.
- Dasyam, R., Pal, S., Rao, V.S., & Bhattacharyya, B. (2015). Time Series Modeling for Trend Analysis and Forecasting Wheat Production of India. *International Journal of Agriculture, Environment and Biotechnology*, 8(2), 303-308. doi:10.5958/2230-732X.2015.00037.6
- Đoković, J., Munćan, M., & Paunović, T. (2018). Quantitative Analysis of Main Indicators of Vegetable Production in the Republic of Serbia, 1th International Scientific Conference Village and Agriculture, Bijeljina, Bosna and Hercegovina, 329-341.
- Đoković, J., Munćan, M., & Paunović, T. (2019). Forecasting maize yield in the Republic of Serbia by using Box-Jenkins methodology. *Economics of Agriculture*, 66(2), 525-540. doi: 10.5937/ekoPolj1902525D
- 12. Eurostat, Retrieved from https://ec.europa.eu/eurostat/web/main/home (14.05.2023)
- 13. Food and Agriculture Organization of the United Nations (FAO), Retrieved from https://www.fao.org/faostat/en/#data (7.05.2023)

- 14. Hamjah, M. A. (2014). Rice production forecasting in Bangladesh: An application of Box-Jenkins ARIMA model. *Mathematical theory and modeling*, 4(4), 1-11.
- Ilić, I., Jovanović, S., & Janković–Milić, V. (2016). Forecasting corn production in Serbia using ARIMA model. *Economics of Agriculture*, 63(4), 1141-1156. doi: 10.5937/ekoPolj1604141I
- Ivanišević, D., Mutavdžić, B., Novković, N., & Vukelić, N. (2015). Analysis and prediction of tomato price in Serbia. *Economics of Agriculture*, 62(4), 951-962. doi: 10.5937/ekoPolj15049511
- 17. Jadhav, V., Chinnappa, R. B., & Gaddi, G. M. (2017). Application of ARIMA model for forecasting agricultural prices. *Journal of Agricultural Science and Technology*, 19, 981-992.
- 18. Kovačić, Z. J. (1995). *Time series analysis*. University of Belgrade Faculty of Economics, Belgrade.
- 19. Mladenović, Z., & Nojković, A. (2021). *Application of Time Series Analysis*. Fifth Edition, University of Belgrade Faculty of Economics, Belgrade.
- 20. Munćan, P., & Živković, D. (2014). *Management of crop production*, University of Belgrade Faculty of Agriculture, Belgrade.
- 21. Mutavdžić, B., & Novković, N. (2016). Analysis and prediction of production parameters of cabbage in Serbia. 21th International Symposium on Biotechnology, Faculty of Agronomy, Čačak, Serbia, 167-172.
- 22. Mutavdžić, B., Novković, N., Vukelić, N., & Radojević, V. (2016). Analyzis and prediction of prices and price parityes of corn and wheat in Serbia. *Journal on Processing and Energy in Agriculture*, Novi Sad, 20(2), 106-108.
- 23. Novković, N., Mutavdžić, B., & Šomođi, Š. (2010). Models for Forecasting in Vegetable Production. *School of Business*, Novi Sad, (3), 41-49.
- 24. Novković, N., Mutavdžić, B., Ivanišević, D., Drinić, L., & Vukelić, N. (2019). Models for forecasting the price of wheat and maize in Serbia. *Journal on Processing and Energy in Agriculture*, 23(3), 138-141.
- Novković, N., Vukelić, N., Šarac, V., & Nikolić, S. (2022). State and Tendencies of Production Characteristics of Wheat and Maize in Serbia. *Journal on Processing* and Energy in Agriculture, 26(2), 68-70. doi: 10.5937/jpea26-37904
- Petropoulos, F., Makridakis, S., Assimakopoulos, V., & Nikolopoulos, K. (2014). 'Horses for Courses' in demand forecasting. *European Journal of Operational Research*, 237(1), 152-163. doi: 10.1016/j.ejor.2014.02.036
- 27. Semenčenko, D., Nikolić, V., & Kutlača, Đ. (2021). The Agrofood Sectors in Smart Specialization Strategies in Serbia and Neigbourhood Countries. *Proceedings of the 37th Scientific Conference of International Importance Technology, culture and development*, Belgrade.
- 28. Siami-Namini, S., Tavakoli, N., & Siami Namin, A. (2018). A Comparison of ARIMA and LSTM in Forecasting Time Series. *In 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 1394-1401. doi:10.1109/icmla.2018.002

- Simić, D., Erić, N., Popović, V., & Đekić, V. (2015). Regional Distrubution of Maize Hybrids in 2014. in the Institute PKB Agroeconomic. *Proceedings of the* 29th Symposium of agronomists, veterinarians, technologists and agroeconomists, Institute of PKB Agroeconomics, Belgrade, 21(1-2), 1-10.
- Starčević, L., & Latković, D. (2006). Prosperity Year for Record Yield of Maize. Proceedings of the *A Periodical of Scientific Research on Field & Vegetable Crops*, Institute of Field & Vegetable Crops, Novi Sad, 42(2), 299-309.
- 31. Statistical Office of the Republic of Serbia (SORS), Retrieved from https://www. stat.gov.rs/ (15.05.2023)
- 32. Suleman, N., & Sarpong, S. (2012). Production and consumption of corn in Ghana: Forecasting using ARIMA models. *Asian Journal of Agricultural Sciences*, 4(4), 249-253.
- United Nations Comtrade Database, Retrieved from https://comtradeplus.un.org/ (18.05.2023)
- 34. United States Department of Agriculture USDA (2021). *The 2021 U.S. Agricultural Export Yearbook*, Retrieved from https://www.fas.usda.gov/sites/ default/files/2022-04/Yearbook-2021-Final.pdf
- 35. Vlahović B. (2015): *Market of agro-industrial products-special part*. University of Novi Sad Faculty of Agriculture, Novi Sad.
- Wihartiko, F. D., Nurdiati, S., Buono, A., & Santosa, E. (2021). Agricultural price prediction models: a systematic literature review. *In International Conference on Industrial Engineering and Operations Management Singapore*, 7-11. doi: 10.46254/AN11.20210532
- Yadav, S., Mishra, P., Kumari, B., Shah, I.A., Karakaya, K., Shrivastri, S., Fatih, C., Ray, S., & Khatib, A.M.G.A. (2022). Modelling and Forecasting of Maize Production in South Asian Countries. *Economic Affairs*, 67(4), 519-531. doi: 10.46852/0424-2513.4.2022.18