

PREDICTION OF SUNFLOWER PRODUCTION PARAMETERS IN SERBIA USING THE ARIMA MODEL¹

Miroslav Nedeljković², Jana Petrović³, Dragan Dokić⁴

Abstract

The main goal of research is analysis and forecast of sunflower production in Serbia, using a time series model, aiming to identify trends and provide accurate forecasts for the short-term period. Research is especially focused on assessment of the potential of using statistical models to predict the production trends of one of the most important oilseeds in Serbia. The paper uses the Autoregressive Integrated Moving Average (ARIMA) model, according to the Box-Jenkins methodological approach. Modeling process has included testing the stationarity of time series, determining the optimal specification of model based on the ACF and PACF functions, estimating the model parameters, as well as checking its adequacy through the use of standard statistical measures of forecast precision. Derived research results suggest that the used model provides a reliable short-term forecast of sunflower production, identifying the key trends in analyzed time frame. Forecasts indicate relatively stable changes in production, with specific oscillations that are characteristic of agricultural production, while depend on the agro-economic and climatic situation. Research results have important practical significance for the organization of agricultural production, regulation of the oilseed market and decision-making within agrarian policy. Based on performed analysis, it can be pointed out that ARIMA models are efficient analytical tool for short-term production forecasting, while additional assessment of economic and climatic variables is advised for future research in order to improve the accuracy of predictions.

Key words: Sunflower, production, forecasting, ARIMA model, Box-Jenkins methodology.

JEL⁵: C53, Q10, E27

- 1 Paper is a part of research financed by the MSTDI RS, agreed in decision no. 451-03-33/2026-03/200009 from 5.2.2026.
- 2 Miroslav Nedeljković, Ph.D., Senior Research Associate, Institute of Agricultural Economics, Volgina Street no. 15, Belgrade, Serbia, Phone: +381 65 447 12 01, E-mail: miroslav_n@iep.bg.ac.rs, ORCID: 0000-0002-7393-2146
- 3 Jana Petrović, Ph.Ds, Faculty of Economics, University of Niš, and Institute of Agricultural Economics, Volgina Street no. 15, Belgrade, Serbia, Phone: +381 60 767 67 80, E-mail: petrovicjana666@gmail.com, ORCID: 0009-0004-7055-5295
- 4 Dragan Dokić, Ph.D., Erdut Municipality, Bana Josipa Jelačića Street no. 4, Dalj, Croatia, Phone: +385 99 219 12 98, E-mail: dragan.dokic79@gmail.com, ORCID: 0000-0001-6321-0716
- 5 Article info: Original Article, Received: 7th March 2026, Accepted: 23rd March 2026.

Introduction

Sunflower is economically important industrial (oilseed) plant, whose processing produces a number of final products (Jeločnik et al., 2021). According to De Oliveira Filho and Egea (2021), sunflower seeds are rich source of nutrients, edible oils, fiber, minerals and phenolic compounds. Besides, sunflower plants are drought resistant, while it can be grown late during the rainy seasons. In addition, they are used in agricultural systems for crop rotation, invariably with other field crops (FBI, 2026). As was pointed out in some studies, global sunflower market has been divided into two segments, i.e. seeds and oil. The need for them is growing due to increasing health awareness, and many health benefits sunflowers brings (VMR, 2026).

So far, many authors have globally used modern forecasting tools in forecasting the production parameters of sunflowers. Thus, Amankulova et al. (2023a) used a combination of multiple linear regression and two different machine learning approaches to predict the sunflower yields in the fields of Southern Hungary. Gurkan et al. (2020) use modern tools to assess the impact of climate change on the possible effects of decision makers in sunflower production in Konya province (Turkey). Also, Amankulova et al. (2023b) develop a machine learning method (Random Forest Regression - RFR) to translate Sentinel-2 spectral bands in sunflower yields, according to crop yields data provided by harvester equipped with a yield monitoring system. Gnatienco, Gnatienco (2024) provide practical evidence for predicting the profitability of complex machines and technology in digital agronomy. In addition to them, Debaeke et al. (2023) conclude that forecasting crop production several weeks before the harvest is of strategic interest for cooperatives that collect, store, and market grains. Besides, they have been using the development of the Sentinel satellite images, combining remote sensing data and statistical modeling to predict sunflower yields in fields of Southwest France.

Regarding the Serbian authors, and their forecasting of sunflower production parameters, Cvejić et al. (2023) predict sunflower yields using different machine learning algorithms. On this occasion, they develop a machine learning model, revealing that the characteristics of certain locality can be used to estimate the yield of sunflower oil, although it largely depends on the weather conditions that affect the oil content and seed yield. Nikolić et al. (2021) predict the trends of production indicators for oilseeds in the area of Vojvodina for the period 2005-2019. Also, Nedeljković et al. (2022) predict the production of this oilseed in Serbia for the period 2005-2021, using the following indicators: Mean Absolute Percentage Error, Mean Absolute Deviation, and Mean Squared Deviation.

Reconsidering the use of ARIMA modeling in predicting production parameters of certain crop, in this case sunflower, as adequate, there are surveyed several studies that justify its use, as well as recommend the model combining with other modern prediction techniques and tools.

Debasis et al. (2019) forecast the production of oilseeds using the ARIMA model in combination with the group method of data processing (GMDH), while Gulizahra (2026) uses ARIMA models to forecast a yield of few field crops until 2030, concluding that this is of particular importance in regions where agricultural productivity is affected by climate change and market dynamics. Bhuyan et al. (2025) forecast the trend of major field crops in the Assam region of India, for the period 2022/23, using ARIMA models. Mentioned authors emphasize the effectiveness of the ARIMA modeling application in agricultural planning and policy development, providing reliable forecasts for strategic decision-making in observed region. Nedeljković (2019) in doctoral dissertation, based on ARIMA modeling, provides a projection of the output of agricultural production in the Republic of Srpska, i.e. several production and economic indicators.

The subject of research in the paper would be the analysis and modeling of time series of data linked to sunflower production in Serbia. It is assumed that they would identify current and future trends in observed crop production. Accordingly, the main goal of the paper is the analysis and forecast of sunflower production in Serbia using time series models. The main research intention is identifying the trends and providing accurate forecasts for the short-term period. Besides, the additional goal is to apply the ARIMA model in sunflower production forecast, while to assess the reliability of the obtained results.

Justification of performed research is based on the economic, agrarian and methodological importance of sunflower production for the national agro-industrial system, as well as on the need for reliable analytical tools that could enable making quality market and development decisions. Also, one of the main limitations of the research would be the additional impact of unforeseen factors in the coming period that could affect sunflower production in Serbia.

Methodology

For the purposes of calculating the basic indicators of descriptive statistics (average, interval of variation, standard deviation, coefficient of variation), as well as the three-year forecast (2026-2028), the twenty-years data series (2006-2025) of sunflower production (data available in the database of the Statistical Office of the Republic of Serbia) were used.

Time series forecasting is one of the most commonly used quantitative methods in agricultural economics. It enables the prediction of production dynamics, yield fluctuations, and commodity price changes based on previous dataset. The analytical framework used in this research has been based on the AutoRegressive Integrated Moving Average (ARIMA) model that was initially developed within the Box-Jenkins methodology. Mentioned methodology remains the leading stochastic forecasting framework in the economic and agricultural domains (Box et al., 2015). ARIMA models have demonstrated outstanding forecasting performance in agricultural production systems characterized by time dependence and stochastic variability (Adebisi et al., 2014). The ARIMA model is defined as:

$$\text{ARIMA}(p, d, q) \quad (1)$$

Where, the parameters are autoregressive (p), integration (d), and moving average component (q). The general formula for the model is:

$$\phi(B)(1 - B)^d Y_t = \theta(B)\varepsilon_t \quad (2)$$

Where, B denotes the return shift operator, while ε_t represents white noise (Hamilton, 1994). ARIMA models particularly stand out for agricultural datasets due to their ability to capture the inertia effects present in crop production and yield dynamics (Hyndman, Athanasopoulos, 2021).

Stationarity is a condition for ARIMA estimation. Agricultural time series often show unstable behavior caused by technological development and climate change. Stationarity is analyzed using the extended Dickey-Fuller test presented by Dickey and Fuller (1981). The equation for the test is represented as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^k \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

Failure to reject the null hypothesis suggests the presence of a unit root which requires differentiation (Enders, 2015).

Model identification comes after autocorrelation diagnostics through:

- Autocorrelation functions (ACF);
- Partial autocorrelation functions (PACF).

These tools enable determination of AR and MA sequences (Box et al., 2015). Autocorrelation structures have been proven useful in modeling agricultural production cycles and yield durability effects (Sharma et al., 2018).

Model parameters are evaluated using Maximum Likelihood Estimation (MLE), which enables statistically efficient estimation of parameters under the assumption

of normality (Hamilton, 1994). The MLE estimate is often used in agricultural forecasting research due to its robustness to small samples (Gujarati, Porter, 2009). Alternative ARIMA specifications are evaluated using the information criteria:

$$\text{AIC} = -2 \ln(L) + 2k \quad (4)$$

$$\text{BIC} = -2 \ln(L) + k \ln(n) \quad (5)$$

Smaller values indicate better model adequacy (Akaike, 1974). Selection based on information criteria is a common practice in the agricultural forecasting literature (Hyndman, Khandakar, 2008).

The independence of the residuals is assessed using the Ljung-Box test (Ljung, Box, 1978). Diagnostic testing guarantees that the residuals act as white noise, which confirms the correct specification of the model (Enders, 2015).

Agricultural systems are usually the subject to external shocks. Therefore, stability of the parameters is analyzed with the CUSUM test (Brown et al., 1975). Examining structural stability significantly increases the reliability of forecasts in agricultural policy analysis. Forecasts are created recursively:

$$\hat{Y}_{t+h} \quad (6)$$

Where: \hat{Y}_t - forecast value; t - current time period; h - forecast horizon.

Prediction uncertainty is measured using the confidence intervals based on the variance of prediction error (Hyndman, Athanasopoulos, 2021). Short-term ARIMA forecasting model, globally has shown exceptional results in forecasting agricultural crop production (Paul et al., 2013). Success of the prediction is evaluated using the following indicators:

a) RMSE (*Root Mean Square Error*)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

Where: y_i - real value; \hat{y}_i - forecast value; n - number of observations.

b) MAE (*Mean Absolute Error*)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

Where: y_i - actual value; \hat{y}_i - forecasted value; n - number of observations.

c) MAPE (*Mean Absolute Percentage Error*)

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (9)$$

Where: y_i - actual value; \hat{y}_i - forecasted value; n - number of observations.

These indicators are widely used in comparison of agricultural forecasts (Makridakis et al., 1998).

Results with Discussion

In 2024, sunflower was produced worldwide on 28,728,506 ha, where the total production has reached the level of about 52,216,784 tons (FAO, 2026). According to the same source, the largest producer was Russian Federation with 17,200,000 tons. It was followed by Ukraine with 10,956,000 tons, and Argentina with 3,895,156 tons. Besides, it should be emphasized that more than 72% of sunflower production is concentrated in Europe (FAO, 2026).

Table 1. Descriptive analysis of sunflower production parameters in Serbia (2006-2025)

Indicators	Average	Variation interval		Standard deviation	Coefficient of variation (%)
		Min.	Max.		
Area (ha)	202,022.15	154,793.00	251,155.00	31,715	15.70
Production (t)	530,438.95	294,502.00	733,706.00	133,650	25.20
Yield (t/ha)	2.56	1.90	3.30	0.38	14.73

Source: Author's calculation based on SORS, 2026.

In Serbia, during the observed period, sunflower was produced in average on 202,022 ha, with the maximum production of 733,706 tons, achieved in 2018. The average yield was at the level of 2.56 t/ha. Production had the largest variations, among the all observed indicators, 25.2% measured by the coefficient of variation (Table 1.). In table could be also seen that the areas and yield of sunflower in Serbia showed relatively stable trend during the analyzed period. Empirical analysis was performed using annual data of sunflower production in Serbia (for the period 2006-2025). The assessed time series show significant variability in production level, mainly affected by climatic factors, technological improvements, and variations in cultivated plots.

Within the analyzed period, sunflower production has been showed a general growth with the presence of several short-term fluctuations. An exceptional increase in production was recorded after 2015, which indicates progress in hybrid seed

technology and expansion in their use. Nevertheless, interannual variability remains evident, which confirms the stochastic characteristic of agricultural production systems. Visual analysis of time series indicated the existence of deterministic trend component, which suggests possible non-stationarity. The stationarity of the production series was tested using the extended Dickey-Fuller test.

Derived results have indicated that the original production series was non-stationary ($p > 0.05$). After applying the first order of differentiation, the null hypothesis of a unit root was rejected ($p < 0.01$), ensuring the stationarity of the transformed series. Therefore, the order of integration is defined as:

$$d = 1$$

This is in line with the series of agricultural production mentioned in earlier forecast analyses.

Model identification was performed by studying autocorrelation (ACF) and partial autocorrelation (PACF) functions, while minimizing information criteria.

Within competing specifications, the ARIMA (1, 1, 4) model demonstrated better statistical performance according to the Akaike and Bayesian information criteria. The estimated parameters showed statistical significance and economic sense, which suggests the existence of persistence effects in the dynamics of sunflower production. This outcome confirms that current production levels are significantly dependent on earlier production shocks and adjustment mechanisms within agricultural systems.

The adequacy of the model was assessed by residual diagnostics using the Ljung-Box test. The obtained results did not indicate statistically significant autocorrelation in the residuals (p -values > 0.05), which suggests the residuals function as white noise. Therefore, the chosen ARIMA specification adequately covers the time dependence in the analyzed series of production.

Indicators of forecast precision, additionally confirmed the reliability of the model, namely:

- RMSE = 71.980 tons;
- MAPE = 9.12%

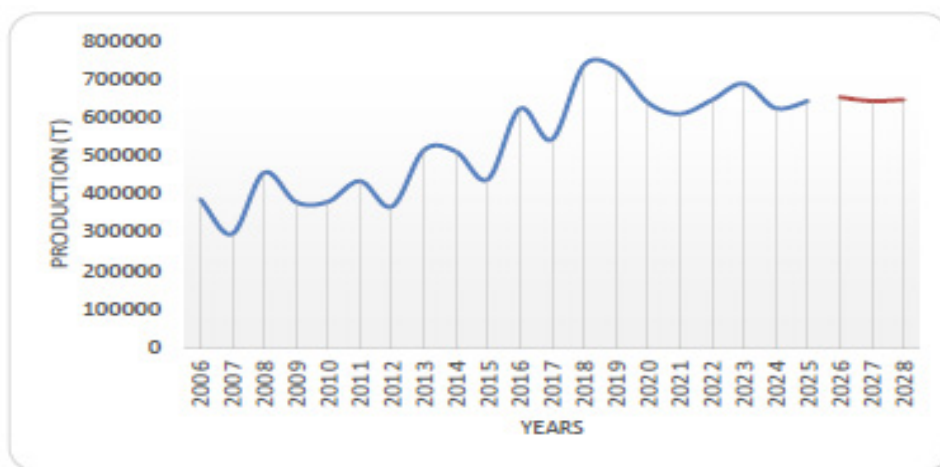
The achieved level of forecast error is considered satisfactory for predicting agricultural production, which is characterized by uncertainty caused by climatic conditions. Based on the analyzed ARIMA model, expected sunflower production in Serbia for the period 2026-2028 could be seen in following table (Table 2.). The prediction results suggest a relative stability of the production level in the medium-term period.

Table 2. Sunflower production forecast for Serbia (2026-2028)

Year	Forecast Production (t)	Lower 95% CI	Upper 95% CI
2026	651,112	488,390	813,833
2027	641,090	454,948	827,232
2028	644,416	439,149	849,682

Source: Author's calculation.

The visualization of the results is shown in Graph 1. Historical production is represented by the blue line, while the forecast for the next three years is represented by the brown line.

Graph 1. Trends and forecasting of sunflower production in Serbia

Source: Author's calculation.

The projection indicates that sunflower production will remain between approximately 640 and 650 thousand tons, without significant upward or downward trend. The stabilization pattern identified by the ARIMA model shows the structural maturity of sunflower production in Serbia. Opposed to earlier phases of expansion, future growth in production is expected to depend mainly on productivity gains, while not on acreage expansion. The widening of confidence intervals over the forecast timeframe indicates the growing uncertainty inherent in agricultural systems that are exposed to:

- climate changes,
- instability of raw material (input) prices,
- policy adjustments,
- dynamic trends at international market of oilseeds.

From economic perspective, stable production levels suggest the preserved competitiveness of sunflower within the oilseed sector in Serbia, continuing its importance for processing industries at national level. The expected stability of production implies that future policies should be aimed at:

- technologies for improving yield,
- hybrids more resistant to the climate change,
- investments in irrigation systems,
- implementation of precision agriculture.

ARIMA based projections provide useful analytical assistance for strategic planning and risk management in agriculture.

Conclusion

In this research, the trend and forecasting of sunflower production in Serbia was studied using the ARIMA time series model. The analysis is based on historical production data, while the model was developed according to the Box-Jenkins methodological framework, which includes identification, assessment and diagnostic verification of model adequacy.

Derived results indicate that the ARIMA model enables accurate short-term forecasting of key sunflower production parameters. Forecast for the next three years indicates a fairly stable production trend, with moderate oscillations specific to agricultural production. Such trend can result from changes in areas under this crop, climatic conditions, as well as economic factors that affect producers' decision.

Research results are important in practice for production planning and proper decision-making in the oilseed industry. Forecasts can improve the management of production resources, the planning of market trends, and development of agrarian policy. Derived results also provide a solid basis for future research that would include additional economic and climate factors in forecasting model.

References

1. Adebisi, A., Adewumi, O., Ayo, K. (2014). Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction. *Journal of Applied Mathematics*, 2014:614342, <https://doi.org/10.1155/2014/614342>
2. Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6):716-723, <https://doi.org/10.1109/TAC.1974.1100705>

3. Amankulova, K., Farmonov, N., Mukhtorov, U., Mucsi, L. (2023a). Sunflower crop yield prediction by advanced statistical modeling using satellite-derived vegetation indices and crop phenology. *Geocarto International*, 38(1), <https://doi.org/10.1080/10106049.2023.2197509>
4. Amankulova, K., Farmonov, N., Mucsi, L. (2023b). Time-series analysis of Sentinel-2 satellite images for sunflower yield estimation. *Smart Agricultural Technology*, 3(2023):100098, <https://doi.org/10.1016/j.atech.2022.100098>
5. Bhuyan, N., Mahanta, S., Sarma, D. (2025). Forecasting Yield of Major Crops in Assam: A Time Series Approach. *Journal of Scientific Research and Reports*, 31(6):932-942, <https://hal.science/hal-05125754/>
6. Box, G., Jenkins, G., Reinsel, G., Ljung, G. (2015). *Time Series Analysis: Forecasting and Control*. 5th edition, Wiley, Hoboken, USA.
7. Brown, R., Durbin, J., Evans, J. (1975). Techniques for testing constancy of regression relationships over time. *Journal of the Royal Statistical Society – Series B: Statistical Methodology*, 37(2):149-163, <https://doi.org/10.1111/j.2517-6161.1975.tb01532.x>
8. Cvejić, S., Hrnjaković, O., Jocković, M., Kupusinac, A., Doroslovački, K., Gvozdenac, S., Jocić, S., Miladinović, D. (2023). Oil yield prediction for sunflower hybrid selection using different machine learning algorithms. *Scientific Reports* 13:17611, <https://doi.org/10.1038/s41598-023-44999-3>
9. De Oliveira Filho, J., Egea, M. (2021). Sunflower seed byproduct and its fractions for food application: An attempt to improve the sustainability of the oil process. *Journal of Food Science*, 86(5):1497-1510, <https://doi.org/10.1111/1750-3841.15719>
10. Debaeke, P., Attia, F., Champolivier, L., Dejoux, J. F., Micheneau, A., Al Bitar, A., Trépos, R. (2023). Forecasting sunflower grain yield using remote sensing data and statistical models. *European Journal of Agronomy*, 142:126677, <https://doi.org/10.1016/j.eja.2022.126677>
11. Debasis, M., Lakshmikanta, D., Kumarjit, M. (2019). Time Series Analysis and Forecasting of Oilseeds Production in India: Using Autoregressive Integrated Moving Average and Group Method of Data Handling Neural Network. *Asian Journal of Agricultural Extension, Economics & Sociology*, 30(2):1-14, <https://doi.org/10.9734/ajaees/2019/v30i230106>
12. Dickey, D., Fuller, W. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4):1057-1072, <https://doi.org/10.2307/1912517>
13. Enders, W. (2015). *Applied Econometric Time Series*. 4th edition, Wiley, Hoboken, USA.

14. FAO (2026). *Data related to global sunflower production*. Food and Agricultural Organization of UN (FAO), Rome, Italy, retrieved at: www.fao.org/faostat/en/#data/QCL/visualize, 24th February 2026.
15. FBI (2026). *Sunflower Oil Market Size, Share & Industry Analysis, by Type (High-Oleic, Mid-Oleic, and Linoleic), End-Users (Household/Retail, Foodservice/HORECA, and Industrial) and Regional Forecast, 2026-2034*. Portal of Fortune Business Insights (FBI), Maharashtra, India, retrieved at: www.fortunebusinessinsights.com/industry-reports/sunflower-oil-market-101480, 2nd March 2026.
16. Gnatienco, V., Gnatienco, G. (2024). Інтеграція методів машинного та глибинного навчання для прогнозування врожайності соняшника. *Управління розвитком складних систем*, 59:225-234, <https://doi.org/10.32347/2412-9933.2024.59.225-234>
17. Gujarati, D., Porter, D. (2009). *Basic Econometrics*. 5th edition, McGraw-Hill, Columbus, USA.
18. Gulizahra, T. (2026). Forecasting Gross Yield in Agriculture Using the Arima Model: The Case of Cereal Crops. *Central Asian Journal of Innovations on Tourism Management and Finance*, 7(1):235-241, <https://doi.org/10.51699/cajtmf.v7i1.1096>
19. Gurkan, H., Shelia, V., Bayraktar, N., Yildirim, E., Yeselekin, N., Gunduz, A., Boote, K., Porter, C., Hoogenboom, G. (2020). Estimating the potential impact of climate change on sunflower yield in the Konya province of Turkey. *Journal of Agricultural Science*, 158(10):806-818, doi: 10.1017/S0021859621000101
20. Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press, Princeton, USA.
21. Hyndman, R., Athanasopoulos, G. (2021). *Forecasting: Principles and Practice*. 3rd edition, OTexts, Melbourne, Australia.
22. Hyndman, R., Khandakar, Y. (2008). Automatic time series forecasting: The forecast Package for R. *Journal of Statistical Software*, 27(3):1-22, <https://doi.org/10.18637/jss.v027.i03>
23. Jeločnik, M., Subić, J., Nastić, L. (2021). *Upravljanje troškovima na poljoprivrednim gazdinstvima [Managing the costs at agricultural holdings]*. Institute of Agricultural Economics, Belgrade, Serbia.
24. Ljung, G., Box, G. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2):297-303, <https://doi.org/10.1093/biomet/65.2.297>
25. Makridakis, S., Wheelwright, S., Hyndman, R. (1998). *Forecasting: Methods and Applications*. 3rd edition, Wiley, NY, USA.

26. Nedeljković, M. (2019). *Predviđanje proizvodno ekonomskih pokazatelja ratarske proizvodnje u Republici Srpskoj [Forecasting production and economic indicators of crops in the Republic of Srpska]*. Doctoral dissertation, Faculty of Agriculture, University in Novi Sad, Serbia.
27. Nedeljković, M., Subić, J., Prodanović, R. (2022). *Prediction of Sunflower Production in the Republic of Serbia*. In: XIII International Scientific Symposium “Agrosym 2022”, proceedings, Faculty of Agriculture, University of East Sarajevo, Lukavica, BiH, pp. 1265-1270.
28. Nikolić, S., Mutavdžić, B., Novković, N., Sredojević, Z., Bjegović, M., Tekić, D. (2022). Tendencies and Prediction of Industrial Plant Production in Serbia. *Economic of Agriculture*, 69(2):317-329, <https://doi.org/10.5937/ekoPolj2202317N>
29. Paul, R., Prajneshu, P., Ghosh, H. (2013). Statistical modelling for forecasting of wheat yield based on weather variables. *Indian Journal of Agricultural Sciences*, 83(2):180-183.
30. Sharma, P., Dwivedi, S., Ali, L., Arora, R. (2018). Forecasting Maize Production in India using ARIMA Model. *Agro Economist - An International Journal*, 5(1):1-6, doi: 10.30954/2394-8159.01.2018.1
31. SORS (2026). *Data related to sunflower production in Serbia*. Portal of the Statistical Office of the Republic of Serbia (SORS), Belgrade, Serbia, retrieved at: <https://data.stat.gov.rs/Home/Result/130102?languageCode=sr-Cyrl>, 24th February 2026.
32. VMR (2026). *Global Sunflower Market Size by Product, by Application, by Geographic Scope and Forecast*. Portal of Verified Market Research (VMR), Boonton, USA, retrieved at: www.verifiedmarketresearch.com/product/sunflower-market/, 2nd March 2026.