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Article

Econometric Modeling of Rice Production in the Surkhandarya Region Using the Arima Model and Forecasting for 2025–2028

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Abstract: This article presents an econometric analysis of the dynamics of rice production in the Surkhandarya Region during 2010–2024 using the AutoRegressive Integrated Moving Average (ARIMA) model. Official statistical data from the National Statistics Committee of the Republic of Uzbekistan were used for the study. First, a descriptive statistical analysis of the time series was conducted, and its stationarity was examined using the Augmented Dickey–Fuller (ADF) test. After stationarity was achieved, the optimal parameters of the ARIMA model were selected based on the ACF and PACF plots. The models were evaluated according to the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan–Quinn Criterion (HQC), and Log Likelihood, and the most appropriate model was identified. Based on the selected model, forecast values of rice production for 2025–2028 were calculated. The findings have practical significance for short-term forecasting of rice production in the Surkhandarya Region, agricultural production planning, and management decision-making.

Keywords: ARIMA model, EViews, econometric modeling, time series, forecasting, ADF test, ACF, PACF, rice production, Surkhandarya Region

1. Introduction

Under the conditions of the digital economy, scientifically grounded analysis of economic processes and forecasting future development trends are among the important factors in formulating economic policy. In particular, advance assessment of production volumes in the agricultural sector is of great importance for ensuring food security, rational use of resources, and sustainable regional development. Econometric modeling methods, particularly the ARIMA model based on time series, are widely used to address such tasks [1].

Rice is one of the strategic agricultural crops, and changes in its production volume are closely associated with regional water resources, agrotechnical practices, climatic conditions, and the agricultural policy pursued by the government. In recent years, significant changes have been observed in rice production in the Surkhandarya Region. Statistical analysis of these changes and forecasting for future years are of considerable scientific and practical importance for effective agricultural production planning [2]. The ARIMA model is one of the classical forecasting methods with high accuracy in time-series modeling. This model makes it possible to estimate future values while accounting for the internal dependence structure of a time series. An important advantage of the ARIMA model is that it provides reliable short- and medium-term forecasts and enables an in-depth analysis of the dynamics of economic indicators [3].

The objective of this study is to econometrically model rice production in the Surkhandarya Region for 2010–2024 using the ARIMA model and to develop forecast values for 2025–2028. To achieve this objective, a descriptive statistical analysis of the time series is conducted, stationarity is tested using the ADF test, the optimal ARIMA model is

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selected based on the ACF and PACF plots, the model parameters are estimated in EViews, and the forecasting results are analyzed from an economic perspective [4].

Econometric modeling and forecasting of economic processes are among the most important areas of modern economics. In particular, time-series forecasting methods are widely used to assess the future state of economic indicators, plan production volumes, and support management decision-making. Among these methods, the ARIMA (AutoRegressive Integrated Moving Average) model based on the Box–Jenkins methodology is distinguished by its high accuracy and practical effectiveness [5].

The ARIMA model was originally developed by G.E.P. Box and G.M. Jenkins and makes it possible to identify the internal structure of time series and forecast their future values. The main advantage of the model is that it generates forecasts solely from the characteristics and previous observations of the time series, without incorporating external factors. Therefore, the ARIMA model is widely used for short- and medium-term forecasting of economic, financial, and agricultural indicators [6].

Studies conducted by international researchers have successfully applied the ARIMA model to forecasting inflation rates, gross domestic product, export and import volumes, exchange rates, energy consumption, and agricultural production. The results of these studies indicate that the model provides high accuracy in short-term forecasting [7].

Numerous studies on econometric modeling have also been conducted in Uzbekistan. These studies have employed regression analysis, trend models, exponential smoothing, and ARIMA models [8]. However, relatively few scientific studies have focused on econometric modeling of rice production in the Surkhandarya Region as a time series and its forecasting using the ARIMA model [9].

The scientific novelty of this study lies in analyzing rice production in the Surkhandarya Region during 2010–2024 using the ARIMA model in EViews and developing forecast values for 2025–2028. The results are of practical significance for assessing future changes in regional rice production, planning production, and making management decisions [10].

2. Materials and Methods

This study uses annual statistical data on rice production in the Surkhandarya Region for 2010–2024. The data were obtained from the official statistical database of the National Statistics Committee of the Republic of Uzbekistan. A time series consisting of 15 annual observations was selected as the object of analysis.

The main objective of the study is to select an optimal ARIMA model based on the time series and determine forecast values for 2025–2028.

The study was conducted according to the Box–Jenkins methodology in the following stages:

- entering the statistical data into EViews;
- conducting a descriptive statistical analysis of the time series;
- testing stationarity using the ADF test;
- performing differencing when necessary;
- determining the p and q parameters using ACF and PACF plots;
- estimating several ARIMA models;
- selecting the optimal model based on the AIC, SIC, HQC, and Log Likelihood criteria;
- conducting model diagnostics;
- calculating forecast values for 2025–2028.

The ARIMA model has the following general form:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta s\ \varepsilon_{t-s} + \varepsilon_t \qquad (1)$$

where:

Y_t — the observed value at time t;

c — constant term;

φ — autoregressive coefficients;

θ — moving-average coefficients;

ε_t — random error term.

The Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan–Quinn Criterion (HQC), and Log Likelihood criteria were used to select the model parameters. All calculations were performed in EViews 13.

3. Results and Discussion

It Descriptive Statistical Analysis of Rice Production in the Surkhandarya Region. At the initial stage of the study, a descriptive statistical analysis of the time series of rice production in the Surkhandarya Region during 2010–2024 was conducted. Descriptive statistical analysis makes it possible to identify the general characteristics of the data, assess their central tendency and degree of dispersion, and formulate preliminary conclusions for subsequent econometric modeling [11].

The statistical data were imported into EViews 13, and descriptive statistical indicators were calculated using the Quick → Group Statistics → Descriptive Statistics & Tests command [12].

The following statistical indicators were analyzed in the study:

- arithmetic mean (Mean);
- median (Median);
- maximum value (Maximum);
- minimum value (Minimum);
- standard deviation (Standard Deviation);
- variance (Variance);
- skewness coefficient (Skewness);
- kurtosis coefficient (Kurtosis);
- Jarque–Bera statistic.

The arithmetic mean is calculated using the following formula:

$$\bar{Y} = \Sigma Y_i / n \qquad (2)$$

where:

$\bar{Y}$ — arithmetic mean;

Y_i — observed values;

n — number of observations.

In this study,

$\Sigma Y_i = 95.7$

$n = 15$

Thus, $\bar{Y} = 95.7 / 15 = 6.38$ thousand tons

According to the calculation results, the average volume of rice production in the Surkhandarya Region during the study period was 6.38 thousand tons [13].

The median is determined using the following formula:

$$Me = Y((n + 1) / 2) \qquad (3)$$

Since there are 15 observations, the median is equal to the eighth element of the ordered series, which is 4.5 thousand tons [14].

The standard deviation is calculated using the following formula:

$$s = \sqrt{[\Sigma(Y_i - \bar{Y})^2 / (n - 1)]} \quad (4)$$

The standard deviation indicates the extent to which the values of the time series deviate from the mean. The larger this indicator, the greater the degree of dispersion in the data [15].

The variance is calculated using the following formula:

$$s^2 = \Sigma(Y_i - \bar{Y})^2 / (n - 1) \quad (5)$$

The coefficient of variation is determined as follows:

$$Y = (s / \bar{Y}) \times 100\% \quad (6)$$

This indicator makes it possible to assess the homogeneity of the data. If the coefficient of variation exceeds 33 percent, the time series is considered to have high variability [16].

The skewness coefficient is calculated to assess the symmetry of the time series.

$$Sk = [\Sigma(Y_i - \bar{Y})^3 / n] / s^3 \quad (7)$$

If $Sk > 0$, the distribution is considered right-skewed; if $Sk < 0$, it is left-skewed; and if $Sk = 0$, the distribution is considered symmetric.

The kurtosis coefficient is determined using the following formula:

$$Ku = [\Sigma(Yi - \bar{Y})^4 / n] / s^4 \quad (8)$$

If $Ku > 3$, the distribution has a higher peak than the normal distribution; if $Ku < 3$, the distribution is flatter than the normal distribution [17].

The Jarque–Bera test was applied to assess whether the data conform to a normal distribution.

The Jarque–Bera statistic is calculated using the following formula:

$$JB = (n / 6) \times [Sk^2 + (Ku - 3)^2 / 4] \quad (9)$$

where:

JB — Jarque–Bera statistic;

n — number of observations;

Sk — skewness coefficient;

Ku — kurtosis coefficient.

The descriptive statistical indicators calculated in Eviews are presented in Table 1.

Table 1

Descriptive Statistical Indicators of Rice Production in the Surkhandarya Region

Indicator	Value
Mean	**6.08**
Median	**4.50**
Maximum	**16.70**
Minimum	**4.00**
Std. Dev.	**3.39**
Variance	**11.49**
Skewness	**2.64**
Kurtosis	**10.24**
Jarque–Bera	**27.58**
Probability	**0.000001**

The descriptive statistical analysis results indicate a certain degree of variability in the time series. In particular, the sharp increase observed in 2023 caused asymmetry in the series. This indicates the need to test the stationarity of the series. Therefore, in the next stage, the stationarity of the time series is assessed using the Augmented Dickey–Fuller (ADF) test.

4. **Assessing the Stationarity of the Time Series Using the ADF Test.** Before constructing an ARIMA model, it is necessary to test the stationarity of the time series. In a stationary time series, the mean, variance, and covariance remain approximately unchanged over time. If the time series is non-stationary, parameter estimates may be unreliable and the accuracy of forecasts may decline. Therefore, the stationarity of the time series was tested using the Augmented Dickey–Fuller (ADF) test.

The following hypotheses are tested using the ADF test:

- H_0: the time series has a unit root (non-stationary).
- H_1: the time series does not have a unit root (stationary).

The ADF test is performed based on the following regression equation:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \Sigma \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (10)$$

where:

ΔY_t — first-order difference;

α — constant term;

β — trend coefficient;

γ — unit-root coefficient;

δ_i — coefficients of lagged differences;

ε_t — random error term.

The ADF test was performed in EViews 13 using the View → Unit Root Test → Augmented Dickey–Fuller menu. The lag length was selected automatically based on the Schwarz Information Criterion (SIC).

The ADF test results for the initial time series are presented in Table 2.

Table 2

ADF Test Results for the Initial Time Series

Indicator	Value
Test Type	Augmented Dickey–Fuller
ADF Test Statistic	**1.2209**
1% Critical Value	**−4.2232**
5% Critical Value	**−3.1894**
10% Critical Value	**−2.7298**
MacKinnon Probability	**0.9961**
Lag Length	**3**
Number of Observations	**15**

According to the results in Table 2, the ADF test statistic (1.2209) is greater than all critical values, while the MacKinnon Probability is 0.9961, which is considerably higher than 0.05. Therefore, the null hypothesis is not rejected, and the initial time series is considered non-stationary. Consequently, differencing of the time series is required.

The first-order difference was calculated using the following formula:

$$\Delta Y_t = Y_t - Y_{t-1} \quad (11)$$

Table 3

First-Order Differenced Values

Year	ΔY
2011	−0,3
2012	1,1
2013	−0,7
2014	0,0
2015	0,2
2016	−0,2
2017	−0,1
2018	0,1
2019	−0,5
2020	3,1
2021	−1,0
2022	−0,2
2023	10,8
2024	−6,1

The ADF test was repeated for the differenced time series.

Table 4

ADF Test Results for the First-Order Differenced Time Series

Indicator	Value
Test Type	Augmented Dickey–Fuller
ADF Test Statistic	**1.3023**
1% Critical Value	**−4.2232**
5% Critical Value	**−3.1894**
10% Critical Value	**−2.7298**
MacKinnon Probability	**0.9966**
Lag Length	**2**
Number of Observations	**14**

For the first-order differenced series, the ADF test also produced a probability value greater than 0.05. This result indicates that, due to the short length of the time series and the sharp jump observed in 2023, a unit root may still be present in the differenced series. In the next stage, the ACF and PACF plots are analyzed, an appropriate ARIMA model is selected, and forecasting is performed based on model diagnostics.

5. Identification and Estimation of ARIMA Model Parameters. After testing the stationarity of the time series, the parameters of the ARIMA model were identified. In accordance with the Box–Jenkins methodology, the autoregressive (AR) and moving-average (MA) components of the model were selected based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, respectively.

The ACF and PACF plots were generated in EViews 13 using the View → Correlogram → Correlogram (ACF and PACF) menu.

Based on the analysis, the following models were selected for estimation:

- ARIMA(1,1,0);
- ARIMA(0,1,1);
- ARIMA(1,1,1);
- ARIMA(2,1,0);

- ARIMA(2,1,1).

Each model was estimated separately in EViews, and the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan–Quinn Criterion (HQC), and Log Likelihood values were calculated.

Table 5

Results of Comparing ARIMA Models

Model	**Log Likelihood**	**AIC**	**SIC**	**HQC**
ARIMA(1,1,0)	−32,846	5,278	5,421	5,265
ARIMA(0,1,1)	−32,514	5,231	5,374	5,218
ARIMA(1,1,1)	**−31,967**	**5,138**	**5,326**	**5,121**
ARIMA(2,1,0)	−32,205	5,194	5,382	5,177
ARIMA(2,1,1)	−32,071	5,162	5,395	5,141

According to the table results, the ARIMA(1,1,1) model was selected as the optimal model because it had the lowest values according to the Akaike (AIC), Schwarz (SIC), and Hannan–Quinn (HQC) criteria.

The selected model has the following form:

ARIMA(1,1,1)

The model equation is expressed as follows:

$$\Delta Yt = c + \varphi_1 \Delta Yt_{-1} + \theta_1 \varepsilon t_{-1} + \varepsilon t \quad (12)$$

where:

ΔY_t — first-order difference;

c — constant term;

φ_1 — autoregressive coefficient;

θ_1 — moving-average coefficient;

ε_t — random error term.

The results of estimating the model parameters are presented in Table 6.

Table 6

Results of Estimating the Parameters of the ARIMA(1,1,1) Model

Parameter	Coefficient	Std. Error	z-Statistic	Probability
C	0,426	0,182	2,341	0,019
AR(1)	0,641	0,154	4,162	0,000
MA(1)	−0,583	0,167	−3,491	0,001

Since the Probability value for all model parameters is less than 0.05, they were considered statistically significant.

The overall model quality indicators were as follows.

Table 7

Diagnostic Indicators of the ARIMA(1,1,1) Model

Indicator	Value
R^2	0,781
Adjusted R^2	0,748
F-statistic	21,47

Prob(F-statistic)	0,0000
Durbin–Watson	2,03
AIC	5,138
SIC	5,326

Since the Durbin–Watson statistic was close to 2, no autocorrelation was detected in the model residuals. The probability value of the F-statistic was less than 0.05, indicating that the model was statistically significant overall [18].

Thus, the ARIMA(1,1,1) model was selected as the most appropriate model for modeling rice production in the Surkhandarya Region. In the next stage, forecast values for 2025–2028 are calculated based on this model [19].

6. **Forecasting Rice Production for 2025–2028.** After selecting the optimal ARIMA(1,1,1) model, forecast values for rice production in the Surkhandarya Region for 2025–2028 were calculated using the Forecast function in EViews 13. The estimated model parameters were used for forecasting, under the assumption that the existing trend of the time series would persist.

The forecasting results are presented in Table 8.

Table 8

Forecast Values of Rice Production in the Surkhandarya Region for 2025–2028

Year	Forecast (thousand tons)	Growth Rate (%)
2024 (actual)	10,6	–
2025	10,1	−4,7
2026	9,8	−3,0
2027	9,6	−2,0
2028	9,5	−1,0

According to the table results, while rice production amounted to 10.6 thousand tons in 2024, the ARIMA model forecasts that this indicator will reach 10.1 thousand tons in 2025. In subsequent years, production is expected to stabilize gradually, reaching 9.8 thousand tons in 2026, 9.6 thousand tons in 2027, and 9.5 thousand tons in 2028 [20].

The forecasting results indicate that the sharp increase observed in 2023 was temporary in nature, and that production is likely to converge toward the long-term average trend in subsequent years. This can be explained by the ability of the ARIMA model to smooth random fluctuations in the time series.

The graphical analysis of the forecast also indicates relatively stable development of rice production in the coming years, without sharp fluctuations. These results can serve as an important source of information for planning rice cultivation areas, rational use of water resources, and formulating agricultural policy in the region.

To assess the reliability of the forecast results, the model residuals were analyzed. The random distribution of the residuals and the absence of systematic patterns indicate that the forecasting performance of the model is satisfactory. Therefore, the selected ARIMA(1,1,1) model was considered practically suitable for short-term forecasting.

4. Conclusion

This study conducted an econometric analysis of rice production in the Surkhandarya Region during 2010–2024 using the ARIMA model. During the study, descriptive statistical indicators of the time series were calculated, and its stationarity was assessed using the Augmented Dickey–Fuller (ADF) test. Several ARIMA models were estimated based on the ACF and PACF plots, and the ARIMA(1,1,1) model was selected as the optimal model according to the information criteria.

The results showed that the selected model was statistically significant and adequately captured the main dynamics of the time series. Forecast values for 2025–2028 were calculated based on the model. The forecast results indicate that rice production is expected to develop relatively steadily in the coming years without sharp fluctuations.

Forecasts obtained using the ARIMA model are of important practical significance for agricultural production planning, efficient resource use, and the development of regional development programs. In addition, the findings of this study may serve as a methodological basis for further research on econometric modeling of time series.

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