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FORECASTING TRENDS OF AGRICULTURAL PRODUCTIVITY IN UZBEKISTAN: AN ARIMA MODEL APPROACH

Boribaeva Qundiz
Toshkent State University of Economics
ORCID: 0009-0004-5697-4282
boribaevaqundiz@gmail.com
PhD, assoc. prof. ***Kodirov Farkhod***
Toshkent State University of Economics
ORCID: 0009-0004-7911-0292
farxod.qodirov@inbox.ru

Abstract. *This study intends to forecast the agricultural commodities in Uzbekistan. The data were obtained from National Statistical Committee of the Republic of Uzbekistan. The study's 15-year duration spans from 2010 until 2024. Box-Jenkin's methodology, known as Auto Regressive Integrated Moving Average (ARIMA) approach was used in this study on a number of specific Uzbek agricultural commodities. According to the methodology requirement for large amount of data points, 10 species of agricultural products were chosen. All the essential steps of the model were utilized methodically for dynamic forecasting 5 periods ahead from 2025onwards. Using various model selection criteria, including Adj R^ 2, the minimum AIC value, and the lowest MAPE values, the study confirmed the accuracy of the model. Barley had the lowest Akaike Information Criterion (AIC) value among these products, while cabbage had the lowest Mean Absolute Percentage Error (MAPE) value.*

Keywords: *agricultural productivity, Box-Jenkin's method, ARIMA model, MAPE, forecasting, AIC.*

O‘ZBEKISTONDA QISHLOQ XO‘JALIGI MAHSULDORLIGINI PROGNOZLASH: ARIMA MODELI YONDASHUVI

Bo‘ribaeva Qundiz
Toshkent davlat iqtisodiyot universiteti
PhD, dots. ***Qodirov Farxod***
Toshkent davlat iqtisodiyot universiteti

Annotatsiya. *Ushbu tadqiqot O‘zbekistonda qishloq xo‘jaligi mahsulotlarini prognozlashni maqsad qiladi. Tadqiqot uchun ma’lumotlar O‘zbekiston Respublikasi Milliy statistika qo‘mitasidan olingan. Tadqiqot 2010-yildan 2024-yilgacha bo‘lgan 15 yillik davrni qamrab oladi. Mazkur ishda ayrim tanlangan qishloq xo‘jaligi mahsulotlari bo‘yicha Box–Jenkins metodologiyasi, ya’ni Avtoregressiv integrallashgan sirpanma o‘rtacha (ARIMA) modeli qo‘llanildi. Metodologiya talabiga ko‘ra yetarli hajmdagi kuzatuvlar zarurligi inobatga olinib, 10 turdagi qishloq xo‘jaligi mahsulotlari tanlab olindi. Modelning barcha muhim bosqichlari tizimli ravishda qo‘llanilib, 2025-yildan boshlab keyingi 5 davr uchun dinamik prognoz amalga oshirildi. Turli model tanlash mezonlari, jumladan tuzatilgan determinatsiya koeffitsienti (Adj R^2), eng kichik AIC qiymati hamda eng past MAPE ko‘rsatkichlari asosida modelning aniqligi tasdiqlandi.*

Natijalarga ko‘ra, mahsulotlar orasida eng past Akaike axborot mezoni (AIC) qiymati arpa mahsulotiga to‘g‘ri keldi, eng past o‘rtacha mutlaq foiz xatolik (MAPE) ko‘rsatkichi esa karam mahsulotida kuzatildi.

Kalit so‘zlar: *qishloq xo‘jaligi mahsuldorligi, Box–Jenkins usuli, ARIMA modeli, MAPE, prognozlash, AIC.*

ПРОГНОЗИРОВАНИЕ СЕЛЬСКОХОЗЯЙСТВЕННОЙ ПРОДУКТИВНОСТИ В УЗБЕКИСТАНЕ НА ОСНОВЕ МОДЕЛИ ARIMA

Борибаева Кундыз
Ташкентский государственный экономический университет
PhD, доц. ***Кодиров Фарход***
Ташкентский государственный экономический университет

Аннотация. *Настоящее исследование направлено на прогнозирование сельскохозяйственных товаров в Узбекистане. Данные для анализа были получены из Национального комитета по статистике Республики Узбекистан. Исследование охватывает 15-летний период с 2010 по 2024 годы. В работе применена методология Бокса–Дженкинса, известная как модель авторегрессии интегрированного скользящего среднего (ARIMA), к ряду отдельных сельскохозяйственных культур Узбекистана. С учетом требований методологии к достаточному объему наблюдений были отобраны 10 видов сельскохозяйственной продукции. Все основные этапы построения модели были последовательно реализованы для динамического прогнозирования на 5 периодов вперед, начиная с 2025 года. Используя различные критерии отбора моделей, включая скорректированный коэффициент детерминации (Adj R^2), минимальное значение информационного критерия Akaike (AIC) и наименьшее значение средней абсолютной процентной ошибки (MAPE), была подтверждена высокая точность модели. Среди рассматриваемых культур наименьшее значение AIC было получено для ячменя, тогда как наименьшее значение MAPE было зафиксировано для капусты.*

Ключевые слова: *сельскохозяйственная продуктивность, метод Бокса–Дженкинса, модель ARIMA, MAPE, прогнозирование, AIC.*

Introduction.

Since agriculture remains one of the key sectors of Uzbekistan’s economy, contributing significantly to GDP, employment, and food security, understanding and predicting its productivity trends is of crucial national importance. According to the State Statistics Committee of Uzbekistan (2024), the agricultural sector accounts for nearly 25% of the country’s total output and provides livelihood for a substantial portion of the rural population. Numerous complicated related factors, including market circumstances, water resource management, climate change variability, and technological innovation, influence agricultural success. In view of this, scientists and government representatives are progressively creating trustworthy quantitative methods to analyze historical trends as well as forecast agricultural output levels in the future. Forecasting in agriculture shows little influence on scientific practice, the establishment of effective policies, risk regulation and the correct allocation of resources. Countries can plan the import and export of goods through reliable forecasts, predict production problems and guarantee the stability of food security. In many scientific studies, the ARIMA model is made too wide for forecasting and the model was created by Box and Jenkins in 1970. This model is a flexible efficient forecasting approach that includes automatic regression, differentiation, and moving averages to control stationary and non-stationary time series data. In articles like this, the value of sophisticated econometric models like ARIMA will drive not only the rationalization of scientific findings but also the sustainable planning of the agricultural economy's dynamics, the efficient use of resources, the preservation of market stability, and the modernization of agriculture. In this study, we aim to apply the Box-Jenkins methodology to develop a forecasting model for selected agricultural commodities in Uzbekistan from 2025 to 2029, based on statistic data. Specifically, we will use the ARIMA model to analyze the time-series data and identify the underlying patterns and trends in carrots, tomatoes, cabbage, onions, cucumbers, potatoes, rice, barley, corn and garlic.

Literature review.

Many economic variables are forecasted using the Box–Jenkins (ARIMA) model in time series analysis. The great accuracy of this approach and its use in agrarian planning and economic decision-making have also been validated by research on forecasting agricultural production in other countries. For example, Padhan (2012). modelled and forecasted agricultural production in India using ARIMA model. Based on this model, he analyzed annual statistical data on agricultural output for the period between 1950 and 2010 and forecasted for another 5 years since 2011. Several model selection criteria were verified. Among these criteria, the products with the lowest AIC value and the lowest MAPE value were identified among the selected products. In another study, Yaseen et al (2005) analyzed and predicted sugarcane yield in Pakistan using ARIMA models. The study demonstrated the models' efficacy and suggested using them to make well-informed decisions on sugarcane production. Based on ARIMA model, Gaddi et al. (2025) forecasted the prices for several cereal crops such as paddy, ragi and maize in Karnataka. Empirical calculations of predicted prices for 2020 showed how effective the ARIMA model is as a method for price forecasting. In the paper by Khalili et al. (2025), the best model for forecasting maize production in Turkey was ARIMA (0,2,1), providing data covering the period 1961-2023.

Yasmin and Moniruzzaman (2024) found that the ARIMA model was best suited for predicting Bangladesh's jute output, yield, and area from 2023 to 2030.The time span of the research included 52 years (1970-2022). The best models were ARIMA (2,0,3) for area, ARIMA (1,0,2) for production, and ARIMA (1,0,3) for yield. BIC, ACF/PACF, and Ljung-Box tests were employed for analyzing the chosen models. Results demonstrated that jute cultivation will go on growing up 7.54 lac hectares in 2023 and 8.30 lac hectares in 2030. This indicator approves that cultivation area will be expected to be 13.85% higher than in 2022. Vice versa, both production and yield will decrease constantly in 2030.

Hamjah utilized ARIMA model to forecast the rice productions of Bangladesh in Aus, Boro, and Aman seasons. The study selected best models for each season, ARIMA (2,1,2) for both Aus and Aman, and ARIMA (1,1,3) for Boro. Obtained results revealed that ARIMA models provide good forecasting for short term analysis.

ARIMA model was used in the study by Tha pa(2022), in order to forecast Nepal's vegetable area, production, and productivity. The most suitable models were ARIMA (0,2,1) for area and production, and ARIMA (0,2,0) for productivity. The study used historical data from 1977/78 to 2019/20 to forecast for 2021/21-2024/25. The results indicated area and production but slightly declining productivity for the predicted years.

Ninety percent of Bangladesh's rural population is actively involved in agriculture, making it a vast country with an agricultural foundation. In the research by Hamjah (2014), the major selected crops were : banana, guava and mango were predicted by using ARIMA method. According to the study, the best-fitting models for predicting the mango, banana, and guava in Bangladesh were ARIMA (2,1,3), ARIMA (3,1,2), and ARIMA (1,1,2). S.Nurman utilized the Box-Jenkins method for forecasting the amount of rice production in Maros Regency. The data were taken from 2001 to 2018. The results showed that the ARIMA (0,2,1) model is a suitable model to predict the amount of rice production. According to forecasting findings, Maros Regency produced 3807.1 tons more rice on average per year.

Bangladesh had a severe food scarcity after independence in 1971. Rice production, the primary crop, decreased as a result of several natural disasters, including floods, droughts, cyclones, and fast growth in population. It was impossible to provide country with rice. Wheat was therefore selected as a substitute food crop during the winter, when natural disasters were mostly avoided. In the study by Abdulla and Hossain, (2015), Box-Jenkin's approach was performed to define the best-fitting ARIMA model that forecasts the production of wheat in both the Kushtia district and Bangladesh. From the analysis, it was found that ARIMA (1,2,1) was the best model for Bangladesh and ARIMA (0,2,1) for Kushtia. Forecasts, based on the received models, entirely matched with the actual production data indicating that both models are dependable for predicting future wheat output in the region.

Maize production in Iraq was focused on to forecast by using ARIMA model in the research by Drebee, et al. (2023, November). Time span of the research included the semi-annual years from 1980-2021. Maize was predicted from 2021 upward 5 years. The obtained results showed a pattern of alternating increases and decreases, coincided with historical production trends. In the second half of 2023 maize production consisted of 585thousand tons, compared to the lowest estimate of 500 thousand tons in the first half of 2022.

Sulieman, (2022). examined Syria's food gap, identifying its features, and developed a suitable forecasting model depending on time series data on the commodity ratio and food shortage from 1986 to 2019. As a result, the food gap indicated a high coefficient of variation of 344,2 %. Food deficiencies were noted for several years, achieving a record high of 3,044 million dollars in 1987. Over the next six years, the gap narrowed to negative values (food surplus), reaching a maximum of -3738 million dollars in 2006. The best model to show how Syria's food gap continued to widen between 2020 and 2025 was ARIMA (0,1,1).

As wheat is the most important crop in Pakistan's economy, the accurate assessment of future production potentials of this crop is significant. Iqbal and Bakhsh et al. (2005) found ARIMA model as effective approach to predict the area and production of wheat in Pakistan up to the year 2022. As a result, production of wheat would be 29774.8 thousand tons in 2002-22.

Amir, (2025). utilized ARIMA model to forecast apple production in Pakistan. ARIMA (2, 1, 2) model was a suitable time series model to forecast the apple production of Pakistan. From the study, it revealed that the apple production of Pakistan was expected to be 697.651 thousand tons in 2030.

In the paper by Shambat, (2025)., ARIMA model was used to forecast cereal production in the Kingdom of Saudi Arabia relying on the gathered data from 1961 to 2021. ARIMA (0,1,1) was the optimal model to perform forecasting. The actual value of cereal food production in 2021 was 1,187,241.77 metric tons, compared to the anticipated value of 1,171,166.24 metric tons; the relative error was around -1.39%. This indicates that the chosen model has a positive impact of fitting.

Research methodology.

The Box-Jenkins (1970) forecasting model, sometimes referred to as the ARIMA model, is used in the current study. ARIMA is an extrapolation technique that requires the underlying variable's historical time series data. The following is an expression for the modeling particular and generic forms. Let Y_t be a discrete time series variable that changes in value over time. The corresponding AR (p) model of Y_t series, which is the generalizations of autoregressive model, can be expressed as:

$$\text{AR(p)}: Y_t = \varnothing_0 + \varnothing_1 * Y_{t-1} + \varnothing_2 * Y_{t-2} + \cdots + \varnothing_p * Y_{t-p} + \mathcal{E}_t \ldots \ldots .... (1)$$

where the response variables at time t are denoted by Y_t

The corresponding variables at various times with delays are $Y_{t-1}, Y_{t-2}, \ldots . Y_{t-p}$

$\varnothing_0, \varnothing_1 \ldots \varnothing_p$ are the coefficients; and $\mathcal{E}_p$ is the error factor

Likewise, the MA (q) model, which is once more an extension of the moving average model, may be defined as follows:

MA(q): $Y_t = \mu_t + \mathcal{E}_t + \delta_1 * \mathcal{E}_{t-1} + \cdots + \delta_q * \mathcal{E}_{t-q} + \mu * t \ldots\ldots\ldots (2)$

Where, $\mu * t$ is the series' constant mean;

$\delta_1 \ldots \delta_q$ are the estimated error term's coefficients.;

$\mathcal{E}_t$ is the error term.

ARIMA models are created by combining both models, and their general shape is as follows:

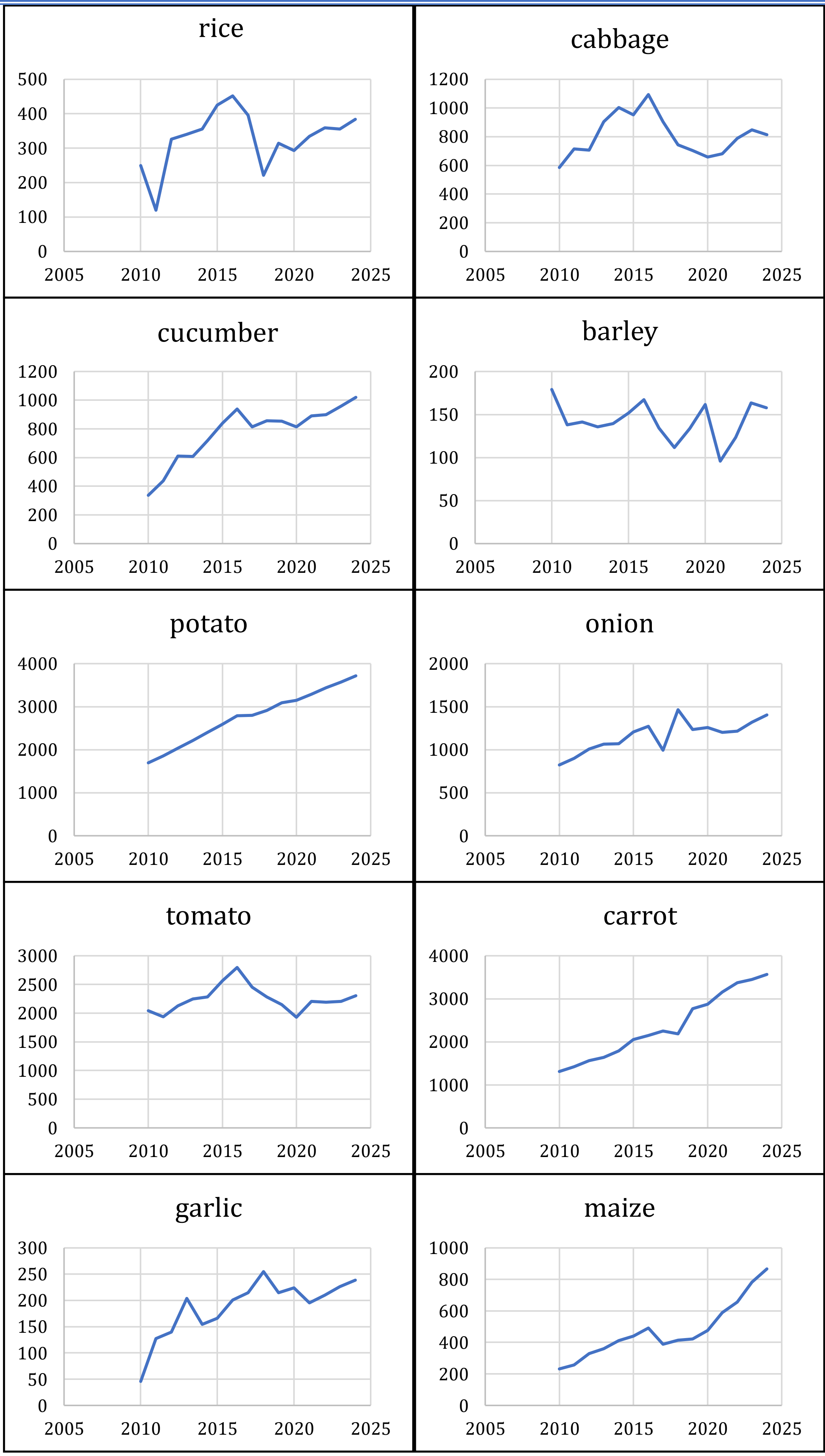
$$Y_t = \emptyset_0 + \emptyset_1 * Y_{t-1} + \emptyset_2 * Y_{t-2} + \cdots + \emptyset_p * Y_{t-p} + \mathcal{E}_t + \delta_t * \mathcal{E}_{t-1} + .. + \delta_q * \mathcal{E}_{t-q} + \mu * t$$

If Y_t is stationary at level or I(0) or at first difference I(1) defines the order of integration, which is referred as ARIMA model. The ACF and PACF are used to determine the order of p and q. The intricacies of the estimating and forecasting procedure are explained below.

The total area of Uzbekistan is 44.89 million hectares, of which 28.15 million hectares are reportedly used for land. The net area farmed is roughly 4,5 million hectares i.e., about 10% of the total reported area. The production of any agricultural items included some process such as farming, harvesting etc. and hence is a time demanding method. A considerable portion of this land is used for the cultivation of major crops such as cotton, wheat, fruits, and vegetables. For forecasting purposes, the report included yearly data on ten distinct agricultural commodities. Data were obtained from National Statistical Committee of the Republic of Uzbekistan. The period of study for tomato, onion, carrot, cucumber, cabbage, potato, maize, barley, rice, garlic is from Dec 2010 to Dec 2024. Other agricultural goods were not taken into consideration here since ARIMA models require a big quantity of data. These variables were measured in units of 000 tons.

Analysis and discussion of results.

The preliminary examination of the selected agricultural products in Uzbekistan revealed a lack of stability in their output over the study period. As shown in Table 1, the production levels of various crops exhibit noticeable variability — some show increasing trends, while others remain irregular or even declining. For example, compared to other commodities, the average output of potatoes (2769.14 thousand tons) and carrots (2370.39 thousand tons) was quite high, indicating that these crops are important to the nation's agricultural sector. Barley averaged 142.32 thousand tons, while garlic averaged 187.69 thousand tons. Most of the series' standard deviation (Std. Dev.) values, especially for corn, potatoes, and carrots, showed significant fluctuations, which allows us to observe how much their production levels vary from year to year. Tomatoes' C.V. value (10.09%) shows that their production levels are nearly constant. Rice (25.41%) and maize (38.01%) show significantly greater deviations, indicating that their production processes are unstable. The skewness (Sk.) and kurtosis values show that most variables deviate from normalcy, both with positive and negative skewness coefficients. For example, tomatoes and corn have positive skewness, showing sporadic spikes in production, while garlic and rice have negative skewness, showing high concentration. The majority of the series are abnormal because of seasonal and climatic variations, according to the Jarque-Bera probability test (J.B.). In general, the cited data show that vegetable growing in Uzbekistan is diverse and irregular, crops such as rice, carrots and corn are more affected by external factors such as weather, market demand and climate change, while tomatoes and onions have a moderate consistency. Through these characteristics, we can see that it points to the need to use reliable forecasting methods such as exponential smoothing or ARIMA to capture the dynamic nature of agricultural products.



Picture 1. A time series plot of certain agricultural goods

Table 1.

Descriptive statistics for various commodities

Variables	Mean	Max	Min	Std. Dev.	Sk.	Kurtosis	J.B. test	Probability	C.V.	Obs.
carrot	2370.393	3566.9	1310.7	773.2892	0.231668	1.667391	1.24408	0.536848	32.62	15
tomato	2247.86	2796.2	1928.5	226.8089	0.83194	3.57514	1.937053	0.379642	10.09	15
cabbage	806.7733	1094	585.3	142.4928	0.436043	2.301474	0.780294	0.676957	17.66	15
onion	1162.233	1464.5	822.5	181.5181	-0.23043	2.279353	0.457324	0.795598	15.62	15
cucumber	773.1267	1019.8	336.8	195.2874	-0.97856	2.977853	2.394247	0.302062	25.26	15
potato	2769.14	3716.9	1694.8	628.7214	-0.2134	1.942819	0.812367	0.666188	22.70	15
rice	328.44	452	119.8	83.46237	-0.95429	3.81892	2.695806	0.259785	25.41	15
barley	142.32	179.1	95.8	22.04512	-0.34803	2.698884	0.359485	0.835485	15.49	15
maize	474.2067	866.8	231.7	180.2587	0.84095	2.926351	1.771382	0.412429	38.01	15
garlic	187.6933	254.9	45.7	53.41825	-1.28262	4.309077	5.183803	0.074878	28.46	15

The estimation of a model: Variables P, d, and q were identified and several combinations of ARIMA models were evaluated using software tools such as Eviews 10 to determine the best specification for each agricultural variable. In this study, statistical criteria were used to select the best models for each Uzbek agricultural commodity. For instance, potatoes were determined to be best suited for the ARIMA (4,0,0) model, which had the greatest Adjusted R2 value (0.987), suggesting a strong match between observed and anticipated values. For carrots, ARIMA (3,0,3) performed the best (Adjusted R^2 = 0.9617). With an Adjusted R2 of 0.1306, barley, on the other hand, showed the lowest fit, suggesting that the model only partially explained its variation. These results are in line with previous research in which the best-fitting ARIMA models for agricultural forecasting were chosen using statistical diagnostics. Iqbal chose ARIMA (1,1,1) and ARIMA (2,1,2) for wheat area and production in Pakistan; Hossain (2006) used multiplicative ARIMA $(3,1,3)\times(2,0,2)_{12}$ and ARIMA $(3,1,2)\times(3,0,2)æ_{2}$ models for pulse prices in Bangladesh. Therefore, in line with these empirical findings, the study's findings verify that, when properly described and statistically tested, the ARIMA approach successfully captures and forecasts agricultural output patterns in Uzbekistan.

Table 2.

Augmented Dickey Fuller unit root tests

Variables	Level		Difference	
	C	with CT	C	with CT
Carrot	0,054966	-2,61949	-4,889366	-4,764248
	0,949	0,278	0,0025	0,0121
Tomato	-2,962212	-3,157238	-3,026758	-2,63068
	0,0698	0,1426	0,0585	0,2789
Cabbage	-3,871526	-4,303949	-2,865734	-2,481452
	0,0167	0,0303	0,0838	0,3287
Onion	-2,426854	-4,186121	-7,029401	-4,035731
	0,1524	0,0267	0,0001	0,0397
Cucumber	-2,392657	-2,311966	-3,46718	-3,643317
	0,1607	0,4021	0,0277	0,0661
Potato	-1,374479	-1,904188	-3,404299	-3,641147
	0,5638	0,5995	0,0309	0,0663
Rice	-2,319944	-2,326857	-5,069035	-5,180327
	0,1794	0,3954	0,0019	0,0065
Barley	-3,706111	-3,875864	-3,383599	-3,20217
	0,0183	0,0467	0,0361	0,1344
Maize	1,087955	-1,869387	-2,584159	-2,815525
	0,9948	0,6037	0,1206	0,2174
Garlic	-3,521509	-3,6846	-5,177108	-4,395255
	0,0238	0,0592	0,0016	0,0308

Stationary vs. non-stationary. Usually, stationary time series data are used with ARIMA models. Therefore, it is crucial to look at the stationarity features of the variables before estimating the forecasting model. To confirm the sequence of integration, the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979) was used at both the level and first difference forms, including and excluding a trend term. Table II presents the estimated outcomes. The majority of the agricultural variables—carrot, tomato, cabbage, onion, cucumber, potato, rice, barley, maize, and garlic—are non-stationary at level but become stationary at first difference, according to the ADF test results. For example, the carrot variable has ADF statistics at levels 0.0549 (C) and -2.6194 (CT), both of which are statistically negligible, while in the first difference the values increase to -4.8893 (C) and -4.7642 (CT), which is important at levels 1% and 5%. Similar results are observed for tomato, cabbage, and potato, where the null hypothesis of a unit root is accepted at level but rejected at first difference, confirming their stationarity after differencing. A few variables such as **barley** and **garlic** show relatively stronger evidence of stationarity at level when a trend component is included in the regression equation, with ADF statistics of **–3.8758** and **–3.6846**, respectively, significant at the 5% level. However, most of the remaining variables — including onion, rice, and cucumber — only become stationary after differencing. This implies that the majority of agricultural production series in Uzbekistan follow an **I(1)** process, meaning they are integrated of order one.

Table 3.

Forecast values with ARIMA model

Variable	ARIMA (p,d,q) Model	Adj R^2	MAPE	AIC values	Forecast values				
					2025	2026	2027	2028	2009
carrot	(1,1,1)	0,96	4,68	14,04	3720,00	3873,20	4026,30	4179,40	4332,60
tomato	(1,1,1)	0,84	3,85	13,15	2270,60	2290,40	2278,60	2285,60	2281,50
cabbage	(1,1,1)	0,72	3,46	12,07	812,80	812,20	811,90	811,80	811,70
onion	(1,0,1)	0,17	14,59	13,34	1303,90	1286,30	1270,50	1256,50	1244,50
cucumber	(1,1,1)	0,74	8,80	12,67	1051,10	1081,20	1110,30	1138,30	1165,30
potato	(1,1,1)	0,99	3,58	12,28	3853,60	3990,20	4126,40	4262,40	4398,20
rice	(2,0,2)	0,58	15,48	11,66	347,62	281,60	253,21	274,86	330,87
barley	(4,0,3)	0,13	13,55	9,67	135,20	145,61	135,35	145,55	135,37
maize	(1,2,1)	0,88	19,50	11,93	975,50	1070,50	1173,60	1272,00	1373,10
garlic	(1,0,1)	0,35	8,66	10,88	227,40	220,00	213,50	207,70	202,70

Diagnostic checking. The right model was found by doing diagnostic tests on the residual term derived from the estimated ARIMA models. The same autocorrelation function (ACF) and partial autocorrelation function (PACF) were applied to the residuals up to particular lag lengths to test whether the coefficients are statistically significant or not, using Box–Pierce Q and Ljung–Box LB statistics, respectively. If the residuals derived from the model behave like a totally random process (white noise), then the estimated ARIMA model is regarded legitimate; otherwise, an alternate model specification must be examined. Furthermore, diagnostic evaluation was also completed using Adjusted R2, Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Mean Absolute Percentage Error (MAPE). The findings reveal that the optimum ARIMA models provided in Table III produce well-behaved residuals with no substantial autocorrelation, supporting the appropriateness of the selected models. In most cases, models exhibit high adjusted R^2 values (e.g., 0.9617 for carrot and 0.987 for potato), relatively low MAPE, and minimum AIC, suggesting that the estimated models are statistically sound and appropriate for forecasting purposes. **Results.** Forecasted values are generated by estimating the suitable models free from specification errors once the ARIMA model's three preceding phases are finished. Table III displays the predicted values derived from the ARIMA models, covering a maximum of five years (2025–2029), as very long-term forecasting may not be reliable due to structural changes and stochastic fluctuations. For instance, the carrot series follows an ARIMA (1,1,1) model with an adjusted R^2 of

0.9617. Projected production values for 2025, 2026, 2027, 2028 and 2029 are 3720, 3873.2 , 4026.3, 4179,4 and 4332,6 units respectively. Projected values and 2024 VAT are absolutely close to each other. The ARIMA (4,0,0) model with the highest R2 value (0.987), is similarly used in potato production, and expectations throughout projected durations also exhibit steady rise. Subsequent years' patterns for tomatoes and cabbage show a saturation or cyclical influence of output. Corn, rice, and garlic exhibit minor fluctuations but mainly stay the same during the scheduled period. Overall, the results demonstrate that the chosen ARIMA models provide highly accurate and statistically valid forecasts, making them useful instruments for short-term agricultural output forecasting in Uzbekistan.

Conclusion and suggestions.

This study found Box-Jenkin's approach – ARIMA methodology best fitting to forecast production of agriculture in Uzbekistan. Ten separate agricultural products—carrots, tomatoes, cabbage, onions, cucumbers, potatoes, rice, barley, corn and garlic-were investigated based on the availability of annual data from 2010 to 2024.The ARIMA algorithm was thoroughly tested in order to predict production values five years in advance (2025–2029). In a similar vein, maize has the highest MAPE and barley has the lowest AIC value, suggesting that some series have more volatility and irregularity in their production patterns. It is important to keep in mind that Uzbekistan's agricultural output is influenced by a variety of external and internal factors, such as rainfall, irrigation systems, climate, fertilizer use, government investment, number of workers, land area availability for cultivation, irrigation canals. Therefore, when analyzing the anticipated values derived from ARIMA models, the ceteris paribus assumption—that other influencing factors remain constant—should be used.

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