Maize Price Forecasting in Nigeria Using ARIMA Model.

Deborah Tosin Fajobi[1], Adedolapo Kemi Ajala[1], Damilola Toluse Adeomi[1], Janet Temitope Ojediran[2] , Kafilat Olasunbo Jubreel[2]

[1]*Department of Agricultural Economics, Ladoke Akintola University of Technology Ogbomoso, Oyo State, Nigeria.*

[2]*Department of Agricultural Extension and Rural Development, Ladoke Akintola University of Technology Ogbomoso, Oyo State, Nigeria.*

Corresponding author: dtodedele@lautech.edu.ng

Abstract

Price stability is a core objective of monetary policy, essential to protecting both producers and consumers. Accurate forecasting plays a critical role in guiding fiscal and monetary tools to achieve this goal. This study employs the ARIMA model to forecast maize prices in Nigeria from March 2024 to April 2026, using monthly secondary data from January 2017 to March 2024, sourced from the National Bureau of Statistics. Data analysis was conducted using ggplot2 and forecast packages in R software. ARIMA(0,2,1) was identified as the best-fitting model based on the lowest AIC and BIC values. Results indicate an overall upward trend, with maize prices projected to rise by approximately 10% by 2026 compared to 2017, despite observable price volatility in the 26-step ahead forecast. These findings suggest the need for Nigeria's monetary policy committee to strengthen trade liberalization and food security measures while effectively applying monetary and fiscal policies to curb inflationary pressures.

Key words: Agricultural Marketing, ARIMA, Price Forecast, Price Stability, Nigeria

Introduction

Price stability remains a cornerstone objective in the formulation and implementation of monetary policy. The removal of fuel subsidies by the Nigerian government has led to anticipated fluctuations in other commodity prices alongside oil (FAO, 2024). Misati et al. (2013) highlight that Nigeria continues to experience persistent inflationary pressures due to shocks in food and oil prices. According to the World Bank's (2019) Commodity Markets Outlook, the prices of commodities like oil and agricultural products have been on the rise, peaking around 2020. Seasonal variations in food production often drive oscillations in food prices in Nigeria. Such frequent and unpredictable price fluctuations influence both consumer and investor decision-making processes.

High prices, while potentially yielding supernormal gains for producers, often signal excessive volatility, which breeds future price uncertainty. Market volatilities deter foreign and local investors from engaging in the commodities market, while consumers face reduced quality of life due to soaring prices. This volatility exacerbates Nigeria's balance of payments issues and hampers economic growth. Conversely, lower export prices could negatively affect the balance of payments, while deflation may reduce business profitability, discouraging investment. Thus, stabilizing price levels is essential for fostering economic growth. Price uncertainty, if unchecked, may undermine investment and economic expansion (Onwude et al., 2023).

Price volatility is an inherent feature of commodity markets, necessitating predictive measures to inform investment strategies and government policies. The Nigeria Federal Competition and Consumer Protection Commission (FCCPC) oversees price regulation (Knaut & Paschmann, 2019). Monitoring

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commodity price indices aids in evidence-based decisions regarding consumption and investment. For instance, investors and manufacturers reliant on specific commodities must understand price trends to make informed choices. The Central Bank of Nigeria (CBN), via its monetary policy committee, aims to stabilize prices and control inflation through mechanisms like Inflation Forecast Targeting (IFT). This forward-looking regime employs Forecasting and Policy Analysis Systems (FPAS) to mitigate unexpected inflationary spikes. The FPAS framework, incorporating quarterly projections and moral persuasion, facilitates corrective policy actions when inflation deviates from the target range of 12.5% to 17.5%, an increase from 33.2% in March (NBS, 2024). Growing demand for time-series data analysis has popularized advanced forecasting models, which address the non-linear nature of commodity prices.

Maize, alongside sorghum and rice, constitutes major cereal crops in Nigeria, with maize emerging as a staple for both household consumption and the animal feed industry. Price spikes in basic foods often cascade to other staples, posing risks to food security, especially given Nigeria's heavy reliance on food imports (Mkhawani et al., 2016). The World Bank estimates that food price surges between 2010 and 2011 pushed 44 million individuals into poverty. Recent global events, including the COVID-19 pandemic and the Russian invasion of Ukraine, have further escalated food prices by 65% since 2020 and 12% in 2022 alone (FAO, 2022). In Nigeria, food inflation reached 24.4% in February 2023, driven by hikes in the prices of cereals, yams, potatoes, and vegetable oil (NBS, 2024).

Since 1999, Nigeria has grappled with farmer-herder conflicts, primarily in the northern and southern regions, leading to loss of life, displacement, and reduced agricultural productivity (Hassan et al., 2018). These conflicts exacerbate food insecurity and contribute to rising agricultural product prices (Odoh & Chilaka, 2012). Factors such as fuel prices, weather conditions, political stability, exchange rates, and global supply dynamics influence price changes, underscoring the need for staple food price forecasting to inform market pricing strategies (Rao et al., 2022).

Agriculture remains the backbone of Nigeria's economy, employing two-thirds of the workforce and contributing over 40% to GDP (FAO, 2018). Despite its significance, challenges such as low productivity and economic shocks—including food price increases—persist. Nigeria's net food import status makes it highly vulnerable to global price surges, highlighting the importance of forecasting food prices to guide policy and reduce import dependency. Rising global food prices have also worsened food and nutrition insecurity, with some regions lacking access to safe, nutritious food (Odusanya et al., 2015).

Forecasting food prices is crucial for governments and stakeholders in the food supply chain. Businesses rely on price predictions for production planning, while agricultural enterprises hedge input and output prices based on anticipated trends. Price fluctuations also impact government programs like school lunch initiatives and nutritional assistance schemes (Kuhns et al., 2015). There is consensus that recent food price surges reflect structural changes—attributable to global population growth, urbanization, and declining agricultural investment in sub-Saharan Africa—rather than temporary spikes (Odusanya, 2015).

Univariate time-series models, particularly ARIMA, have been widely applied to forecast agricultural commodity prices, informing decisions on consumption, imports, and exports. These models have proven effective in identifying patterns and trends in

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economic time series. However, limited research exists on the price dynamics of selected grains in Nigeria for specific periods. This study addresses this gap by developing models to forecast maize prices across Nigerian states, providing insights for traders, consumers, and policymakers. Such forecasts enable informed decision-making, promoting price stability and economic planning. The study aims to identify patterns in price dynamics and develop models for future trends in maize prices, with broader implications for understanding systematic patterns and random noise in time-series data. A summary of related studies are shown in Table 1.

The studies show that ARIMA is a common approach for forecasting commodity prices and inflation. Though, there exists upward trend for most commodity forecast, there are pockets of volatile situations. Given, the recent upsurge in fuel prices following years of COVID-19, this study attempts to forecast the price of maize for the next 12 months to guide policy makers on approriate food policy measures.

Material and methods

Model Description

An Autoregressive Integrated Moving Average (ARIMA) model, which generates t data, is a component of a univariate economic time series like Y. Three order parameters, abbreviated p, d, and q, are typically used to define an ARIMA model. The model's autoregressive component forecasts the observed values based on historical data. The number of lags permitted in the model is indicated by the autoregressive parameter, p.

For example, ARIMA (n, 0, 0) is represented by;

$$Yt = \propto_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_n Y_{t-n} + \varepsilon_t \dots\dots (1)$$

where α_o to α_n are the model parameters. The d component of the model indicates the degree of differencing *(I(d))* in the integrated component. The moving average component of the model, q indicates the residual of the model as a function of previous residual terms.

$$Yt = \beta_o + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_n \varepsilon_{t-n} + e_t \dots\dots..(2)$$

When the three components are combined, the ARIMA model, which can be written in linear form as:

$$Yt = c + \alpha_1 Y_{dt-1} + \alpha_2 Y_{dt-2} + \alpha_n Y_{dt-n} + \beta_o + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_n \varepsilon_{t-q} + e_t$$

There are two alternative process of setting up an ARIMA model (Box and Jenkin 1976). The first procedure involves the following steps:

1. Plotting the data and checking for outliers, stationarity and/or the need for variable transformation
2. Differencing until the variable is stationary.
3. Using differenced series to find appropriate p and q ARIMA parameters.
4. Fitting the appropriate ARIMA (p, d, q) to the original data
5. Verifying that the best available model has been estimated.
6. Forecast

The routes to be taken in respect of the second alternative include:

1. The use of an iterative automated algorithm with as many different models as possible and later

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identifies the best model with appropriate information criteria.
2. Fitting the ARIMA (p, d, q) to the original data
3. Verifying that the best available model has been estimated.
4. Forecast

The second approach is followed in this paper using the automated algorithm in forecast package in R software

Measures of Accuracy

Let Y_t to be *th* observation and ht the forecast, where t= t 1,2,.......,n the following measures of accuracy were used to assess the forecast performance of the models used in this study:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - h_t|$$

$$MAPE = 100 * \frac{1}{n}\sum_{t=1}^{n}(|Y_t - h_t|/|Y_t|)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(|Y_t - h_t|)^2}$$

Where MAE is the mean absolute error, MAPE the mean absolute percentage error and RMSE the Root Mean Square Error. The criterions to judge for the best model is relatively small of MAE and RMSE.

Results and discussion

Descriptive Analysis

Descriptive Statistics

The summary statistics for maize prices in Nigeria between 2017 and 2024 are presented in Table 2. The average prices of maize during this period were irregular, ranging from ₦40.399 (in 2008) to ₦135.768 (in 2013). The variance showed an even wider range, from 12.081 (in 2016) to 6948.16 (in 2007). Similarly, the average monthly price of yellow maize remained relatively low, varying between ₦68.672 (in February) and ₦96.413 (in November), as shown in Table 3. Despite the lower average prices, the variance in yellow maize prices was considerable, though less pronounced than that of beans, ranging from 674.564 (in October) to 4968.15 (in May).

Figure 1 highlights trends in monthly maize prices in Nigeria from 2017 to 2023, revealing significant fluctuations coupled with a distinct upward trend over the years. This trend suggests that maize prices are heavily influenced by both seasonal and systemic factors. Seasonal patterns are evident, with sharp price increases in March, May, and October, likely reflecting reduced supply before harvest cycles. In contrast, other months exhibit relative price stability, consistent with increased supply during or immediately after harvest periods. These trends align with Nigeria's climatic seasons, where the wet season (April to October) facilitates crop production, and the dry season (November to March) leads to reduced supply, driving prices upward. The long-term upward trend in maize prices can be attributed to inflation, rising input costs (e.g., fertilizer, labor, and fuel), Nigeria's reliance on food imports, and global commodity price volatility. This finding contrasts with the random patterns observed in time series plots of rice production in Nigeria, as reported by Aina et al. (2015). The sudden "hops" observed in the time series data may be linked to naturally occurring phenomena such as climatic conditions, and security challenges like the Boko Haram insurgency, as well as quasi-experimental conditions (Chatfield, 2003). Other studies provide additional insights into factors driving price instability, Fluctuations in soybean cultivation acreage are influenced by political instability, oil price volatility, population growth, and climate change Abu et al., (2015). Moreover, Huka et al. (2014) concluded in their study that price fluctuations were tied to the nature of agricultural products, currency exchange rate volatility, and inadequate infrastructure. Mustapha & Culas (2019) concluded that price instability is further exacerbated by climatic and socio-political factors. The series plot for maize prices suggests the presence of a potential food crisis, consistent wth the findings of Ikeokwu (2019), who emphasized that African countries are experiencing the worst food crisis in three decades. Furthermore, the wide variability margins in commodity prices, particularly for maize, underscore persistent factors such as seasonal fluctuations, changes in input prices, marketing technologies, and consumer preferences (Kassim, 2012). These factors collectively contribute to the sustained instability in maize prices, emphasizing the urgent need for targeted policy interventions to address food insecurity and stabilize market dynamics.

Figure 2 depicts the trend in maize prices in Nigeria between 2017 and 2024, highlighting significant changes over the years. The price movement can be characterized by three distinct phases: stability, gradual increase, and sharp escalation.

From year 2017 to 2019, maize prices were relatively stable, with minimal fluctuations. This stability suggests that supply and demand dynamics during this period were balanced, possibly due to favorable production conditions and stable market operations. Beginning in the year 2020, there was a noticeable upward trend in prices. This shift could be attributed to economic disruptions caused by the COVID-19 pandemic, which impacted supply chains, increased production costs, and strained logistics. Other contributing factors may include rising inflation and climatic variability affecting yields. From year 2021 onward, maize prices exhibited a steep and sustained rise, with a significant surge in late 2022 and into 2023–2024. This period reflects the interplay of several systemic and external factors in the country like economic pressures which includes inflation, currency devaluation, and rising costs of agricultural inputs such as fertilizers and fuel likely exacerbated production costs. Also, insecurity in major maize-producing regions may have disrupted farming activities and market supply chains. Unpredictable weather patterns likely contributed to reduced agricultural output while volatility in global markets may have further influenced domestic maize prices. Increasing population and urbanization likely heightened demand, straining existing supply. The final segment of the trend shows a dramatic acceleration in maize prices. This suggests deepening supply shortages, possibly due to compounded effects of structural challenges, including poor infrastructure, inefficiencies in market regulation, and persistent climatic and security issues. The trajectory also reflects the vulnerability of Nigeria's food systems to economic and environmental shocks.

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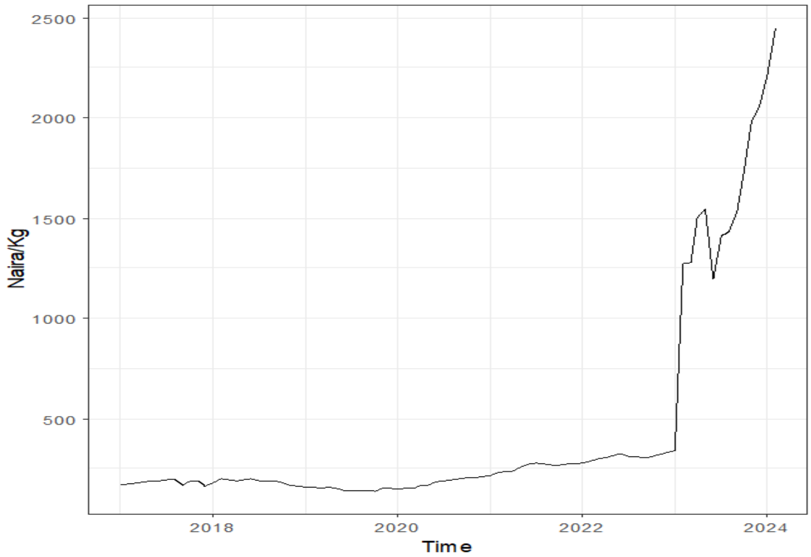

Figure 1: Evolution of Maize Price in Nigeria: 2017-2024

The Results of the ARIMA Model

The R forecast package's auto-ARIMA function is used to automatically determine the ideal p, d, and q components of the ARIMA model. The automated process demonstrates that 0, 2, 1 are the ideal p, d, and q values for the ARIMA model. The model incorporates a differencing of order two in addition to zero auto-regressive and moving average terms of one. The price of maize in kilograms per naira is predicted by the model up to April 2026. The results are presented in Tables 5 and 6. Table 6 shows an overall upward trend, with maize prices projected to rise by approximately 10% by 2026 compared to 2017.

Conclusions

A widespread practice and essential component of monetary policymaking is forecasting. A sound policy option that is supported by evidence should rely on accurate projections that can be achieved if the best model with the highest predictive accuracy is applied. ARIMA (0,2,1) (AIC = 1046.51, MAE = 3.31%, MAPE = 4.65%, MASE = 0.128%) was constructed for this study using the Box-Jenkins model building approach. The model performs well with monthly maize prices in Nigeria because all of the prediction metrics fell below the permitted range of five percent. In addition, the 26-step forward projections showed that the price of maize appeared to be unstable. Nevertheless, ARIMA models are only useful for short-term forecasting and are unstable for long-term projections. Based on the findings, the following recommendations are suggested:

1. Government should improve rural security to allow farmers easy access to their farms during planting and harvest seasons
2. Enhance farmers access to improve extension services and climate smart practices to boost maize production
3. Allow limited tariff-free importation of maize to stabilize local maize prices.

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Table 1: Summary of Previous Studies

Authors	Commodity	Model	Period	Results
Ahumada *et al.,* (2016)	Food prices for corn, soybeans and wheat.	Robust approaches and recursive schemes	2008 – 2014	Inclusion of interaction terns improves the model
Ajetomobi and Adesola, (2019)	Cocoa production	ARIMA	1900-2025	cocoa production would fall by more than 20% in 2025 relative to 2017
Venkatesh *et al.,* (2017)	Maize monthly price	ARIMA	April 2002 to May 2017	Maize price increase in the next 5 month
Osuolale, *et al.,* (2017)	Inflation rate	ARIMA	2006 to 2015	Increase in inflation rates from 2016 to 2018
Doguwa and Alade (2013)	the consumer price index	SARIMA and SARIMAX	July 2001 to Septembe r, 2013	SARIMA predicts inflation better than SARIMAX
Saxena & Mhohelo (2020)	Retail prices of maize	ARIMA	June-2018 to May-2019	Increase in maize price in Tanzania markets
Taofik *et al.,* (2020)	Price of beans, yellow maize and local rice	ARIMA	2006-2015)	Instability in prices of beans, maize and local rice
Adams *et al.,* (2023)	Monthly price of maize and sorghum	ARCH and GARCH	January 1960 – August 2022.	Volatility in monthly prices of maize and sorghum
Zalkuwi *et al.,* (2024)	wholesale maize and rice price	ARIMA.	(2017 – 2023)	Upward trend in the prices of the commodities
Liu et al., (2024)	Water quality prediction, water pollution control, and sustainability.	ARIMA	Monthly and daily data: 2021 – 2021	ARIMA model goodness of fit and forecast accuracy depend on sample size and prediction time

Note: ARIMA indicates AutoRegressive Integrated Moving Average, SARIMA indicates Seasonal AutoRegressive Integrated Moving Average, ARCH indicates Autoregressive Conditional Heteroskedasticity, GARCH indicates Generalized Autoregressive Conditional Heteroskedasticity.

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Table 2: Average Maize Price in Nigeria: 2017-2024

Year	2017	2018	2019	2020	2021	2022	2023	2024
Mean	41	72	40	55	74	95	135	165
SE	1	24	1	2	2	1	17	19
Variance	12	6948	15	53	74	9	3822	4832

Note: SE, standard error and Var, variance. The prices are in Naira/Kg

Table 3: Seasonal Variation in Maize Prices in Nigeria: 2017-2024

Mth	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Mean	71	68	73	73	88	88	77	82	73	69	96	92
SE	10	10	10	10	23	23	12	12	9	8	20	21
Var	1085	1021	984	929	4968	4944	1498	1348	866	674	3870	4300

Note: Mth means month, SE, standard error and Var, variance. The prices are in Naira/Kg

Table 4: Results of ARIMA model

Arima parameter	**Coefficient**	**Standard error**	**t-value**	**Pvalue**
AR1	27.72089	13.03194	2.127	0.03
MA1	1.58921	0.54736	2.903	
Log likelihood	-521.25		0.00475	
Akaike information criteria	1046.51			
Sigma squared	14241			

****Significant at 1% and *at 5% respectively**
Source: Field survey, 2024

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Table 5: Forecast of Monthly Average Maize Price in Naira/Kg in Nigeria

Month	Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Mar	2024	1056.573	447.0684	1666.077	117.2847	1995.861
Apr	2024	1093.516	484.0121	1703.021	154.2283	2032.804
May	2024	1104.984	495.48	1714.489	165.6962	2044.272
Jun	2024	1059.1	449.5958	1668.604	119.812	1998.388
Jul	2024	1088.271	478.767	1697.776	148.9833	2027.559
Aug	2024	1092.281	482.7771	1701.786	152.9933	2031.569
Sep	2024	1101.934	492.4296	1711.438	162.6459	2041.222
Oct	2024	1130.632	521.1281	1740.137	191.3444	2069.92
Nov	2024	1170.45	560.9495	1779.954	231.1621	2109.738
Dec	2024	1178.967	569.4625	1788.471	239.6788	2118.255
Jan	2025	1252.368	644.4527	1860.283	315.5289	2189.206
Feb	2025	1403.737	795.8224	2011.652	466.8986	2340.576
Mar	2025	1231.821	616.0005	1847.642	282.7992	2180.843
Apr	2025	1268.765	652.9441	1884.585	319.7428	2217.787
May	2025	1280.233	664.412	1896.053	331.2107	2229.254
Jun	2025	1234.348	618.5278	1850.169	285.3265	2183.37
Jul	2025	1263.52	647.6991	1879.34	314.4978	2212.541
Aug	2025	1267.53	651.7091	1883.35	318.5078	2216.551
Sep	2025	1277.182	661.3616	1893.003	328.1604	2226.204
Oct	2025	1305.881	690.0602	1921.701	356.8589	2254.903
Nov	2025	1345.699	729.8779	1961.519	396.6766	2294.72
Dec	2025	1354.271	738.3946	1970.036	405.1933	2303.237
Jan	2026	1427.616	812.6686	2042.563	479.4941	2375.292
Feb	2026	1578.986	964.0385	2193.933	631.3098	2526.662
Mar	2026	1407.069	783.6158	2030.523	446.2845	2367.854
Apr	2026	1444.013	820.5594	2067.467	483.2282	2404.798

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