Application of SARIMA Model on Forecasting Wholesale Prices of Food Commodities in Tanzania
A Case of Maize, Rice and Beans

Agnes B. Joseph[1], Godfrey Edward Mpogolo

1 Assistant Lecturer
Department of Management Studies, Tanzania Institute of Accountancy (TIA), Tanzania
agness.joseph@tia.ac.tz

Abstract:

This research used a time series model called the Seasonal Autoregressive Integrated Moving Average (SARIMA) technique to model and forecast wholesale prices of Tanzania`s key food crops, notably maize, rice, and beans. The SARIMA model was selected due to its ability of fitting data with seasonality. Monthly wholesale prices data of the three crops between February 2004 to October 2021 in Tanzania were retrieved from the website of the Bank of Tanzania (BoT), resulting in 213 observations on each crop. The data from February 2004 to October, 2020 were used to fit a SARIMA model and data of November 2020 to October 2021 were used to validate the model. The results show that SARIMA (0,1,2) $(1,0,1)_{12}$, SARIMA (0,1,0) $(1,1,1)_{12}$ and SARIMA (0,1,0) $(0,1,1)_{12}$ are the most suitable models for forecasting wholesale prices of maize, rice and beans respectively. The model's accuracy was tested using Mean Absolute Percent Error (MAPE), and the results were found satisfactory. The results reveal that maize, rice, and beans will all have higher peak prices in February 2022, with TZS 54,083/=, TZS 167,258/=, and TZS 180,117.68/= per 100kg, respectively. Therefore, SARIMA (0,1,2)$(1,0,1)_{12}$, SARIMA (0,1,0)$(1,1,1)_{12}$ and SARIMA (0,1,0) $(0,1,1)_{12}$ models could serve as a useful tool for modelling and forecasting monthly wholesale prices of maize, rice and beans respectively in Tanzania.

Keywords: SARIMA, Price; Maize, Rice, Beans, Tanzania.

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1.0 Introduction

One of the most critical challenges facing smallholder farmers in developing nations is price instability (Mgale, 2021). Consumers can be harmed by fluctuations in agricultural commodity prices, which can lead to income insecurity among farm households (Gu et al, 2022). Because it is impossible for a producer to predict the exact amount of future pricing or the change in the sale schedule, high price variances might have an impact on production decisions (Sirisupluxana and Bunyasiri, 2018). In developing nations such as Tanzania, instability (variation) in the price of staple foods is a major source of risk, according to Minot (2013), especially for poor households in rural and urban regions who spend roughly 70 per cent of their income on consumption.

Agriculture is the primary economic sector in Tanzania, contributing significantly to the country's overall economy. By 2020, the sector had contributed 26.9 per cent of the national GDP (Economic Survey Report, 2020). The crop sub-sector contributed 15.4 per cent of the GDP, livestock per cent, fisheries 1.7 per cent, and forest 2.7 per cent. The sector is the country's principal source of employment, food production, industrial raw materials, and foreign earnings.

According to the National Sample Census of Agriculture (NSCA) estimates for the 2019/20 agricultural year, Tanzanians planted cereal crops on a total of 7,448,402 hectares, with smallholder farmers owning 7,406,207 ha (99.4%) and large-scale farms owning 42,195 ha (0.6%). Maize was the most widely planted crop, with 4,931,111 ha (66.6 per cent) followed by paddy (1,688,241 ha (22.8 per cent) and sorghum (512,888 ha; 6.9%), and other cereal crops (bulrush millet, finger millet, wheat, and barley) with 273,967 ha (3.7 per cent).

Maize is the most important cereal crop in the country, accounting for 70 per cent of all cereals produced, with per capita consumption estimated to be 80–135 kg/person/year (USDA, 2018). Maize has also been listed as a critical crop for improving food security and income (FAOSTAT, 2015). Rice is the second most important staple food in Tanzania. Its per capita consumption is around 16 kilograms, and it accounts for around 8 per cent of Tanzanian caloric intake (Minot, 2010). Rice is the most commercialized crop, and it is commonly consumed in hotels, restaurants and other establishments (Gabagambi, 1998).

However, many of the regular rice customers in hotels and food vending machines are individuals who are reasonably wealthy enough to afford its higher price than maize meals. Furthermore, the popularity of rice in restaurants and organizations stems mostly from its convenience in catering (Gabagambi, 1998). Beans are the most widely planted and consumed pulse among all Tanzanian pulses (NSCA, 2019/20). It is a staple food in most Tanzanian rural homes. It is the primary source of protein for the majority of Tanzania's low and middle-income households (FEWSNET, 2021). In most households, they are both food and income-generating crops.

According to Xiong and Bao (2018), agricultural commodities such as maize, rice and beans play an important part in people's everyday life. Agricultural commodity price fluctuations have been increasingly extreme in recent years, resulting in significant social consequences. An increase in costs will put a strain on people's food budgets, affecting their overall well-being. Large price fluctuations will increase the risk of production for the farmer, increasing the number of risks that must be managed (Zhang et al, 2020).

Forecasting agricultural commodities' future prices is an important topic in the agricultural arena because it not only provides decision makers with pricing information for agricultural commodities in advance, but it also reduces agricultural market uncertainty and risks (Wang, Yue, Wei, & Lv, 2017). Many scholars have worked on developing and testing models for estimating the pricing of agricultural food crops around the world. Kumar et al. (2011) compared the forecasting performances of H-WES and Seasonal ARIMA time-series methodology for forecasting onion prices in Bangalore market and proved that the ARIMA model can be successfully used for modelling and forecasting the monthly price of onion in Bangalore. Burark and Sharma (2012) confirmed the suitability of ARIMA models in agricultural price forecasting.

Kirimi, (2016) conducted a study on modelling the volatility of maize prices using ARIMA models to achieve the most effective and satisfactory model for forecasting the prices of maize in Kenya. He used monthly maize prices data for five years taken from the Kenya National Bureau of Statistics and National Cereals and Produce Board Archives. The study showed that ARIMA

(1, 2, 2) was the most suitable and competent model for predicting future maize prices in Kenya. Hassan et al. (2014) fitted a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast the wholesale price of rice based on monthly data from July 1975 to 2011. They fitted SARIMA $(1, 1, 1)(0, 1, 1)_{12}$ which was found to be the best model by considering the model with minimum values of root mean square, normalized Bayesian Information Criterion (BIC) and mean absolute percentage error. The diagnostic checking for the fitted model was done by using the Ljung-Box test which indicated that it was adequate.

Kibona and Mbago, (2017) sought to estimate general maize prices in Tanzania using ARIMA model for the maize data from 2004 to 2017 obtained from the Bank of Tanzania. The study found that ARIMA (3, 1, 1) was the effective model for predicting maize general prices built on minimum Akaike's Information Criterion (AIC) and the fitted model was brought suitably into being using Ljung-Box test. Urassa (2017) conducted a study on factors influencing maize crop production at a household level in Rukwa region Tanzania. The study found that maize crop continues to play an important role in most households' livelihood.

The ARIMA model is one of the most representative and extensively used models in time series prediction, and it is simple to apply because it only uses endogenous factors rather than exogenous variables. The ARIMA model has the drawback of not fitting observations with seasonality (Panga et al, 2020). To address this, (Box et al, 1976) provide a broad a variant of ARIMA model that takes into account seasonality. The model's name is SARIMA (Seasonal ARIMA). Due to the incorporation of seasonal elements, SARIMA is believed to be substantially more powerful than ARIMA in forecasting complex data fields with seasonality and cycles (Zhang X et al, 2013). In the agricultural field, the SARIMA model has been used widely to forecast the prices of agricultural products. For example, Sahu et al (2020) forecasted prices of paddy in Chhattisgarh state India, *Mathenge (2019)* studied *Forecasting of tomatoes wholesale prices in Nairobi in Kenya,* and Tamilselvi and Naidu (2020) studied forecasting of veritable arrivals and wholesale prices of Koyumbedu Market in India. To the best of our knowledge, there are few studies in the forecasting domains of the prices of maize, rice and despite its importance. In addition, none of the previous studies performed in Tanzania used SARIMA methodology to forecast wholesale prices of maize, rice and beans. To address these gaps, this study used the SARIMA model to perform a time series analysis of the wholesale prices of maize, rice and beans in Tanzania.

Therefore, this study aimed to find the most accurate SARIMA model for forecasting maize, rice, and bean wholesale prices in Tanzania, and then to use it to estimate future wholesale prices for the next year. The data used are the monthly wholesale prices of three selected food crops obtained from the Bank of Tanzania website from February 2004 to October 2021. Price forecasting will aid in making more informed decisions and will play a key role in coordinating crop supply and demand. As a result, forecasting prices for Tanzania's primary food crops will be beneficial to producers, consumers, processors, other stakeholders as well as market authorities and institutions.

2.0 Methodology

The research was carried out throughout Tanzania. The country was purposefully selected because her economy is mostly dependent on agriculture, which accounts for around 26.9 per cent of the national GDP (Economic Survey Report, 2020). This study considers three important food crops, maize, rice and beans. Maize is Tanzania's most important cereal crop, followed by rice, while beans are the most commonly consumed pulse and a primary source of protein for the majority of the country's poor and middle-income households.

This study used a longitudinal research design of the type of time series design. The basic goal of time series analysis is to create a mathematical model that can predict future observations based on the existing data, allowing for more realistic models to be created.

This study employed secondary time series data from the Bank of Tanzania's (BOT) Monthly Economic Review, downloaded from www.bot-tz.org, for the period from February 2004 to October 2021, yielding 213 observations with no missing values, satisfyin g the requirement of the Box-Jenkins method which requires at least 50 observations. The data gathered were the national average wholesale price per hundred kg (in Tanzanian shillings). In Tanzania, the BOT releases significant macroeconomic information, including commodity prices.

The data was analysed by using the Seasonal Autoregressive Integrated Moving Average (SARIMA) method in IBM SPSS software.

2.1 SARIMA Models

SARIMA models are an adaption of Autoregressive Integrated Moving Average (ARIMA) models that are designed to fit seasonal data. That is, their design takes into account the series' underlying seasonality. Seasonality in a time series refers to a regular pattern of changes that repeats over time. The basic form of the SARIMA model is represented as $SARIMA(p,d,q)\times(P,D,Q)s$, where AR is the autoregressive model and MA is the moving average model; and represent the non-seasonal and seasonal differencing respectively; , , and represent the orders of non-seasonal and seasonal autoregressive and moving average respectively; represents the length of the seasonal period of observed series. The formula of the $SARIMA(p,d,q)\times(P,D,Q)s$ model as demonstrated by Wu et al (2022)

$$\phi(B)(B^S)(\Delta^d \Delta^D y_t) = \theta(B)\Theta(B^S)\varepsilon_t$$

$$E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_t^2, \quad E(\varepsilon_t \varepsilon_s) = 0, \quad s \neq t$$

$$E(y_t \varepsilon_t) = 0, \ \forall_s < t$$

$$\phi(B) = 1 - \alpha_1 B - \alpha_2 B^2 - \ldots \alpha_p B^p$$

$$\theta(B) = 1 - \beta_1 B - \beta_2 B^2 - \ldots \beta_q B^q$$

$$\Phi(B^s) = 1 - \alpha_1 B^s - \alpha_2 B^{2s} - \ldots \alpha_P B^{Ps}$$

$$\Theta(B^s) = 1 - \beta_1 B^s - \beta_2 B^{2s} - \ldots \beta_Q B^{Qs}$$

Where represents the backward shift operator, y_t represents the actual wholesale price at time t, and ε_t represents the residual errors from the SARIMA model, $\phi(B)$ is the non-seasonal p order autoregressive coefficient polynomial, and $\theta(B)$ is the non-seasonal q order autoregressive coefficient polynomial. Ina addition, $\Phi(B^s)$ denotes the seasonal P order autoregressive coefficient polynomial, $\Theta(B^s)$ denotes the seasonal Q order autoregressive coefficient polynomial.

To fit the models, the full-time series data were divided into two parts: a training set consisting of data collected from February 2004 to October 2020, and a validation set consisting of data gathered from November 2020 to October 2021. The process of the SARIMA model involves four steps (Xu et al, 2017)): Firstly, a time series graph of monthly wholesale prices of maize, rice, and bean was constructed from 2004 to 2021 to evaluate its intuitive stationarity. If the original data are not stationary, then non-seasonal difference or seasonal difference should be utilized to change the time series into stationarity. The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the differenced series were used to check for stationarity. Secondly, the ACF and PACF were used to determine the ordering of p, q, P, and Q. The model parameters were estimated using the least square method. Thirdly, the goodness-of-fit of the SARIMA models was assessed using the Bayesian information criterion (BIC). The model with the lowest BIC values was deemed the best. The residuals' Ljung-Box Q test, ACF, and PACF were utilized to determine whether the residuals sequence was white noise. Finally, the optimal model was utilized to make a prospective prediction, and the model's accuracy was assessed using mean absolute percentage error (MAPE).

$$MAPE = \frac{1}{n}\sum \frac{|Y_{OBS} - Y_{PRED}|}{Y_{OBS}}$$

Where Y_{OBS} represents the observed wholesale prices, Y_{PRED} represents predicted prices and n represents the number of months for forecasting.

3.0 Results and Discussion

The observed series of Wholesale prices of maize, rice and beans (February 2004 to October 2021) shows that the series is non-stationary and there are seasonal fluctuations in the dataset (Fig. 1). We performed the first order non-seasonal difference and seasonal difference with a period of 12 to eliminate the trends and seasonal effects respectively. According to the characteristics of the Autocorrelation function (ACF) and partial autocorrelation function (PACF) (Fig. 2 to Fig 4), the models were selected, and the models in which the residuals were not likely to be white noise were excluded. Based on the results of the goodness-of-fit test statistics, it is confirmed that SARIMA (0,1,2)(1,0,1)12, SARIMA (0,1,0)(1,1,1)12 and SARIMA (0, 1, 0)(0,1,1)12 were the optimal models for maize, rice and beans respectively, as they had lower BIC value. The estimation of the SARIMA model parameters and the testing results were presented in Tables 1 to 3. Furthermore, the ACF and PACF of the residuals of SARIMA (0,1,2)(1,0,1)12, SARIMA (0,1,0)(1,1,1)12 and SARIMA (0, 1, 0)(0,1,1)12for maize, rice and beans respectively fell within the random confidence intervals, indicating that the residuals did not deviate from a zero mean white noise process (Fig 5). Finally, the results of the Ljung-Box Q test for the models (Table 4) suggest that the residuals were white noise sequence. The results of Goodness-of-fit test demonstrate that the performance of the fitted models, SARIMA (0,1,2)(1,0,1)12for maize, SARIMA (0,1,0)(1,1,1)12for rice and SARIMA (0, 1, 0)(0,1,1)12for beans, were reasonably well.

Furthermore, the SARIMA (0,1,2)(1,0,1)12, SARIMA (0,1,0)(1,1,1)12 and SARIMA (0, 1, 0)(0,1,1)12 models were applied to forecast the monthly wholesale prices for maize, rice and beans respectively, for 14 months from November, 2021 to December, 2022 (Table 5). Figures 6 to 8 and Table 6 show the comparison of the actual and the forecasted wholesale prices of maize, rice and beans respectively. It can be evidenced that the forecasted values track the actual series quite well during the period. The accuracy of the models was calculated based on the MAPE. The outcomes show that the proposed models can forecast the real maize, rice and beans prices with the accuracy of MAPE values of 25.57, 5.86 and 12.19 per cent respectively. This means maize forecasts are on average 25.57 per cent off, rice forecasts are 5.86 per cent off, and bean forecasts are 12.19 per cent off. The estimation error is within the acceptable bounds.

The forecast results show that maize and rice prices are expected to increase from November 2021 to February 2022 and then from September to December 2022, with higher prices of TZS 54,083/= and TZS 167,258/=, per 100 kg, in

February 2022. Bean prices are expected to increase from November 2021 to January 2022, then from September 2022 to December 2022, peaking in February 2022 at TZS 180.117. 68 / = per 100Kg.

Autocorrelation function (ACF) and partial autocorrelation function (PACF) for monthly wholesale prices of maize after first order non-seasonal difference and first order seasonal difference. Autocorrelation function (ACF) and partial autocorrelation function (PACF) for monthly wholesale prices of rice after first order non-seasonal difference and first order seasonal difference. Autocorrelation function (ACF) and partial autocorrelation function (PACF) for monthly wholesale prices of beans after first order non-seasonal difference and first order seasonal difference.

4.0 Conclusion and Recommendations

This study aimed to model and forecast the wholesale prices of three of Tanzania's most useful agricultural commodities: maize, rice, and beans by Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The best model was found to be SARIMA $(0,1,2)(1,0,1)_{12}$, SARIMA $(0,1,0)(1,1,1)_{12}$ and SARIMA $(0, 1, 0)(0,1,1)_{12}$ for maize, rice and beans respectively. The models were then employed to forecast the wholesale prices of the three crops, and their forecasting ability was found to be satisfactory, as shown in Figures 6 to 8 and Table 6. The forecasted prices of maize and rice show an increase from November 2021 to February 2022 and then from September to December 2022 with the higher prices of TZS 54,083/= and TZS 167,258/= per 100kg respectively, in February 2022. For beans, the forecasted prices show an increase from November 2021 to January 2022 and then from September 2022 to December 2022 with a peak price in February 2022 where the price was TZS 180,117. 68/= per 100Kg.

The projected future prices of Tanzania's three major crops can assist both farmers and customers in obtaining price information in advance for agricultural commodities, allowing them to make informed selling and buying decisions. Future forecasting research may investigate better predicting approaches that take into account seasonality and other pricing influencing factors such as weather, import-export gap, and other factors, amongst many others, to improve forecasting accuracy.

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Appendix 1

Table 1. Model Selection Criteria for Tentatively Selected SARIMA Models for Maize.

Model	BIC	P-Value
(1,1,2) (1,0,1)	16.530	0.739
(1,1,1) (1,0,1)	18.077	0.203
(1,1,2) (0,0,1)	16.539	0.573
(1,1,0) (1,0,1)	16.533	0.087
(0,1,2) (1,0,1)	16.523	0.325
(0,1,2) (1,0,0)	16.533	0.206
(1,1,1) (0,0,1)	16.560	0.082

Table 2. Model Selection Criteria for Tentatively Selected SARIMA Models for Rice

Model	BIC	P-Value
(1,1,0) (1,1,1)	17.515	0.009
(1,1,0) (1,1,2)	17.544	0.008
(1,1,0) (0,1,1)	17.540	0.001
(0,1,0) (1,1,1)	17.507	0.000
(0,1,2) (2,1,1)	17.568	0.007
(1,1,2) (1,1,1)	17.565	0.011
(1,1,1) (0,0,1)	17.732	0.010

Table 3. Model Selection Criteria for Tentatively Selected SARIMA Models for Beans.

Model	BIC	P-Value
(0,1,0) (2,1,1)	17.272	0.625
(0,1,0) (1,1,1)	17.241	0.728
(0,1,0) (0,1,1)	17.209	0.759
(0,1,1) (0,1,2)	17.241	0.730
(0,1,0) (0,1,2)	17.265	0.778
(0,1,1) (0,1,1)	17.233	0.826

ACF and PACF of residuals series of the SARIMA $(0,1,2)(1,0,1)_{12}$ for maize, SARIMA $(0,1,0)(1,1,1)_{12}$ for rice and SARIMA $(0, 1, 0)(0,1,1)_{12}$ for beans, models.

Table 4. Model Selection Criteria for Tentatively Selected SARIMA Models for Beans.

Model Statistics											
Model	Number of Predictors	Model Fit statistics						Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	MAPE	MAE	Normalized BIC	Statistics	DF	Sig.	
Maize	0	0.26	0.965	3635.376	5.411	2415.281	16.523	15.808	14	0.325	0
Rice	0	0.552	0.979	6085.65	3.574	4307.993	17.507	47.905	16	0	0
Beans-	0	0.437	0.986	5314.672	3.564	4060.269	17.209	12.649	17	0.759	0

Table 5. Forecasted Prices of Maize, Rice and Beans from November 2021 to December 2022.

	Maize	**Rice**	**Beans**
Date	Forecast	Forecast	Forecast
Nov-21	49890.87	154382.5	176702.30
Dec-21	52684.56	158133.02	179580.56
Jan-22	53679.76	162252.27	181627.09
Feb-22	54083.94	167258.1	180117.68
Mar-22	51655.05	162157.56	172530.58
Apr-22	51260.01	166012.74	170731.13
May-22	49724.61	156657.76	171065.01
Jun-22	49189.15	146938.44	170708.99
Jul-22	48814.35	141856.84	166241.49
Aug-22	48621.08	138319.48	166076.08
Sep-22	48990.14	141028.65	168944.14
Oct-22	50272.96	144344.32	172405.44
Nov-22	51747	147335.04	176974.94
Dec-22	53678.18	150868.26	179785.88

Table 6. Comparison of observed and predicted wholesale prices

	Maize		Rice		Beans	
Date	**Actual Price**	**Predicted Price**	**Actual Price**	**Predicted Price**	**Actual Price**	**Predicted Price**
Nov-20	58,012.86	58869.82	144,331.96	142176.85	208,249.07	203901.77
Dec-20	56,892.10	62051.63	147,654.22	145963.36	205,164.05	207740.53
Jan-21	56,866.75	63155.91	144,285.35	149855.58	198,531.57	210928.26
Feb-21	51,450.06	63984.19	124,829.00	151880.57	195,554.56	210025.92
Mar-21	47,963.39	61371.15	142,013.00	152448.98	180,879.96	203439.85
Apr-21	44,973.16	61157.55	143,055.27	156060.69	181,977.04	202008.51
May-21	43,545.82	59558.13	136,447.64	149374.86	177,437.92	203239.54
Jun-21	42,757.78	59041.03	134,233.92	141249.12	173,637.69	203653.54
Jul-21	43,371.02	58594.90	136,569.84	136969.81	170,511.20	199608.43
Aug-21	44,811.66	58287.62	140,136.72	134035.48	173,213.29	199772.33
Sep-21	44,365.89	58736.24	141,520.16	138603.64	168,501.21	203705.11
Oct-21	48,171.52	59966.73	151,867.78	145395.50	172,065.48	207689.77
	MAPE=25.57		MAPE=5.86		MAPE=12.19	