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Temporal Forecast of Maize Production in Tanzania: An Autoregressive Integrated Moving Average Approach

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Abstract

This paper aims to model and forecast maize production in Tanzania, emphasizing its crucial contribution to the agricultural sector. Utilizing secondary data on annual maize production in Tanzania from 1961 to 2021, measured in tonnes and sourced from the FAO database, the study employs statistical techniques such as unit root tests, the ARIMA model, and the Ljung-Box test for a comprehensive analysis. The optimal model for forecasting maize production in Tanzania is identified as ARIMA (5,1,5), and the adequacy assessment confirms its effectiveness in predicting maize production values. The ten-year forecast reveals an intermittent pattern, offering valuable insights into anticipated trends. While not explicitly developing an existing theory, this research enhances the understanding of maize production dynamics in Tanzania through the application of advanced statistical methods. Policymakers, agricultural stakeholders, and researchers can leverage these findings to enhance agricultural productivity and food security in Tanzania.

Keywords: Arima, forecast, maize, production, Tanzania

1. Introduction

1.1 Introduce the Problem

Maize is a cereal crop globally, and holds a critical position in the agricultural gross domestic product, contributing not only to human sustenance but also to livestock feed worldwide. In Tanzania, maize production serves as a primary food source for rural and urban populations and as a vital source of income. According to the Food and Agriculture Organization (FAO) report (2021), maize production plays an essential role in ensuring food security for both rural and urban dwellers in Tanzania. A decline in maize production, therefore, poses a threat to food security at the household level, emphasizing the need for constant monitoring (Jha et al., 2020). Monitoring and forecasting maize production in Tanzania become imperative to gain insights into production patterns and make informed decisions.

Consistently ranking among the world's top 25 maize-producing countries, Tanzania is recognized as a maize producer in SSA (Twilumba, Ahmad, and Shausi, 2020). Maize, acknowledged as a staple food, is consumed by both rural and urban populations in Tanzania (Laudien et al., 2020; Baijukya et al., 2020). Food crop production, particularly maize, influences global food security, a crucial concern for human survival (Quaye et al., 2012; Ngongi and Urassa, 2014). The potential consequences of food insecurity are apparent, with an estimated 355 million people in SSA projected to face food shortages by 2050 (Rwanyiziri et al., 2019).

In recent years, forecasting food crop production, especially maize, has become increasingly challenging due to climate extremes such as heavy rains, storms, and floods (Liu and Basso, 2020). Despite collaborative efforts by stakeholders and the government, Tanzania encounters difficulties in achieving sustainable crop yields and ensuring food security (Mkonda and He, 2017). While considerable attention has been given to modeling cereal production, limited knowledge exists, particularly regarding forecasting maize yield to address food insecurity.

Time series methods, focusing on forecasting future values based on past observations, have found extensive application in various fields, including economics, agriculture, and climate studies (Enders, 2015; Box and Jenkins, 1970; Petrevska, 2017; Yildiran & Fettahoğlu, 2017; Uwamariya and Ndanguza, 2018; Mgaya, 2019; Bezabih et al., 2023). In Tanzania, few studies have modeled and forecasted maize production using different methods. Examples include Ogutu et al. (2018), utilizing dynamic ensemble seasonal climate forecasts, and Laudien et al. (2020), employing LASSO regression for maize yield forecasting, Lwaho and Ilembo (2023), who forecasted maize production. This paper aims to contribute to this knowledge by modeling annual maize production in Tanzania and forecasting future production over the next ten years using the ARIMA model, selected for its proven reliability in sequential series prediction.

1.2 Explore the Importance of the Problem

Maize stands as a linchpin in global food security, catering to both human and livestock consumption and serving as a crucial raw material for biofuel production (Nyaligwa et al., 2017). It is particularly pronounced in Sub-Saharan Africa (SSA), where maize emerges as a primary cereal crop in over half of the countries and ranks among the top two cereals in more than three-quarters of these nations (Suleiman & Kurt, 2015; Faostat, 2021).

1.2.1 Economic and Agricultural Significance

Maize production holds immense economic importance, contributing substantially to the agricultural gross domestic product worldwide. In Tanzania, the maize goes beyond mere sustenance, as it serves as a vital source of income for many households. The Food and Agriculture Organization (FAO) (2021) underlines the essential role of maize production in ensuring food security for both rural and urban populations in Tanzania. Any decline in maize production, therefore, poses a direct threat to food security at the household level (Jha et al., 2020).

1.2.2 Tanzania's Role in Global Maize Production

Tanzania consistently ranks among the top 25 maize-producing countries globally, making it a contributor to SSA's maize production (Twilumba, Ahmad, & Shausi, 2020; Suleiman & Kurt, 2015). The consumption of maize as a staple food spans both rural and urban populations, emphasizing its critical role in the Tanzanian diet (Laudien et al., 2020; Baijukya et al., 2020).

1.2.3 Food Security and Global Concerns

Food crop production, with maize at its forefront, plays a pivotal role in global food security, a concern vital for human survival (Quaye et al., 2012; Ngongi & Urassa, 2014). The potential repercussions of food insecurity are alarming, with an estimated 355 million people in SSA projected to experience food shortages by 2050 (Rwanyiziri et al., 2019).

1.2.4 Escalating Challenges: Climate Extremes and Food Security

The task of forecasting food crop production, especially maize, has become increasingly challenging due to climate extremes, such as heavy rains, storms, and floods (Liu & Basso, 2020). Despite ongoing efforts by stakeholders and the government, Tanzania grapples with the challenge of achieving sustainable crop yields and ensuring food security (Mkonda & He, 2017).

1.2.5 Limited Research on Maize Yield Forecasting in Tanzania

While time series methods have seen widespread application in various fields, including economics, agriculture, and climate studies, there is a paucity of research specifically focused on modeling and forecasting maize production in Tanzania. Previous studies, such as those by Ogutu et al. (2018) and Laudien et al. (2020), have utilized different methodologies, yet a comprehensive understanding of maize yield forecasting, especially in response to food insecurity, remains limited.

1.3 Describe Relevant Scholarship

Several authors have modeled and forecasted maize productions using the autoregressive integrated moving average (ARIMA) model. Among them are: Sharma et al. (2018) forecasted maize production in India, Verma (2018) forecasted maize yield in India using ARIMA and state space models, Urrutia et al. (2017) forecasted quarterly production of rice and corn in the Philippines using seasonal ARIMA model, Nasiru and Sarpong (2012) forecasted maize production in Ghana using ARIMA model, Badmus and Ariyo (2011) forecasted cultivated areas and production of maize in Nigeria, In their recent work, Lwaho and Ilembo (2023) delve into the application of the ARIMA (AutoRegressive Integrated Moving Average) model for forecasting maize production in Tanzania. The findings indicate that the ARIMA (1,1,1) model emerges as the most fitting choice for forecasting maize production. The efficacy demonstrated by this selected model in predicting maize production for the upcoming years substantiates its suitability and warrants a recommendation for practical application. In a study by Laudien et al.

(2020), an empirical investigation was conducted to devise a statistical maize yield forecast model specific to Tanzania. The research employed regional yield data and climatic predictors spanning the period from 2009 to 2019. The model demonstrated notable success in predicting both yield and absolute yields at the sub-national level, providing forecasts approximately 6 weeks before the harvest. This study, therefore seeks to model and forecast maize production in Tanzania. This will help relevant stakeholders monitor the production pattern of maize and make informed decisions.

1.4 State Hypotheses and Their Correspondence to Research Design

H_0**:** The ARIMA model does not offer a good fit for forecasting the maize production data.

H_a**:** The ARIMA model offers a good fit for forecasting the maize production data.

For the Augmented Dickey-Fuller (ADF) test:

- H_0: The time series data of maize production has a unit root (it is not stationary).
- H_a: The time series data of maize production is stationary.

For the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test:

- H_0: The time series data of maize production has no unit root.
- H_a: The time series data of maize production has a unit root.

2. Method

The data and the statistical techniques adopted to achieve the objectives of the study are presented in this section. The statistical techniques presented here include Unit root tests, autoregressive integrated moving average (ARIMA) model, and Ljung-Box test.

2.1 Data and Source

Secondary data on the annual production of Maize in Tanzania from 1961 to 2021 were utilized in this study. The data were measured in tonnes. The data were obtained from the FAO database. The data were accessed on 28th August 2023 via the link https://www.fao.org/faostat/en/#data/QCL.

2.2 ARIMA Model

A generalization of the ARMA model to handle non-stationary time series data is the ARIMA model. The ARIMA model is often denoted as ARIMA (*p*, *d*, *q*), where *p* is the order of the autoregressive (AR) process, *d* is several times the series needs to be differenced and *q* is the order of the moving average (MA) process. For a non-stationary series, *p* is identified using the partial autocorrelation function (PACF) of the differenced series and *q* is identified using the autocorrelation function (ACF) of the differenced series. The ARIMA model on a time series

can be written in a general form as

$$\Delta^d \text{Maize}_{t-1} = \phi_1 \Delta^d \text{Maize}_{t-1} + \phi_2 \Delta^d \text{Maize}_{t-2} + .. \phi_p \Delta^d \text{Maize}_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_q \varepsilon_{t-q} \quad (1)$$

where Δ is the backshift operator, *d* is the different order, $\phi_1, \phi_2 \ldots \phi_p$ are the parameters of the AR part of the model, $\theta_1, \theta_2 \ldots \theta_p$ are the parameters of the MA part of the model and ε_t is a white noise process (Box et al., 2008). To obtain the best ARIMA (*p*, *d*, *q*) model, the model with the smallest values of Akaike information criterion (AIC), corrected AIC (AICc), Bayesian information criterion (BIC), and highest value of log-likelihood is selected.

2.3 Unit Root Tests

The stationarity of time series data is essential when performing time series analysis. The Augmented Dickey-Fuller (ADF) Dickey and Fuller, (1979) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) unit root tests were employed to test the stationarity of the maize production data in this study. The null hypothesis for the ADF test is that the time series data has a unit root (it is not stationary) and the null hypothesis for the KPSS test is that the time series data has no unit root. The decision for the rejection or acceptance of the null hypothesis depends on the level of significance one is working with. The 5% level of significance was used in this study. Thus, the null hypothesis is rejected if the *p-value* is less than 0.05.

2.4 Test for Model Adequacy

After selecting the best ARIMA model from the competing models, it is imperative to examine whether the selected model provides a good fit to the data set. This can be performed by examining whether the autocorrelation in the model residuals is insignificant. The Ljung-Box test developed by Ljung and Box (1978) is used to examine the model adequacy in this regard. The test statistic for the Ljung-Box test is

$$Q(\hat{r}) = m(m+2)\sum_{k=1}^{h}\frac{\hat{r}_k}{m-k}, \tag{2}$$

where m is the number of observations, $\hat{r}$ is the estimated autocorrelation at lag k and h is the number of lags being tested. The test statistic is distributed as a chi-square random variable. The test statistic is insignificant if the *p-value* is larger than 0.05. Insignificant autocorrelation in the residuals of the best model implies that the model is adequate.

3. Results and Discussion

Table 1 presents the descriptive statistics of the maize production in Tanzania from 1961 to 2021. The minimum, maximum, and average productions over the entire period were 488000, 703900, and 2750266 tonnes. The coefficient of skewness suggests that the maize production is right skewed and the negative value of the excess kurtosis is an indication that the production data less peaked compared to the normal distribution.

Table 1. Descriptive statistics

Statistic	Maize
Minimum	488000
Maximum	7039000
Average	2750266
Skewness	0.798
Excess Kurtosis	-0.555

The time series plot of the data in Figure 1 shows an increasing trend over the period. The autocorrelation function (ACF) plot exhibits some significance suggesting that the maize production data is not stationary. The partial ACF (PACF) plot shows some significant spikes at lags 1 and 2.

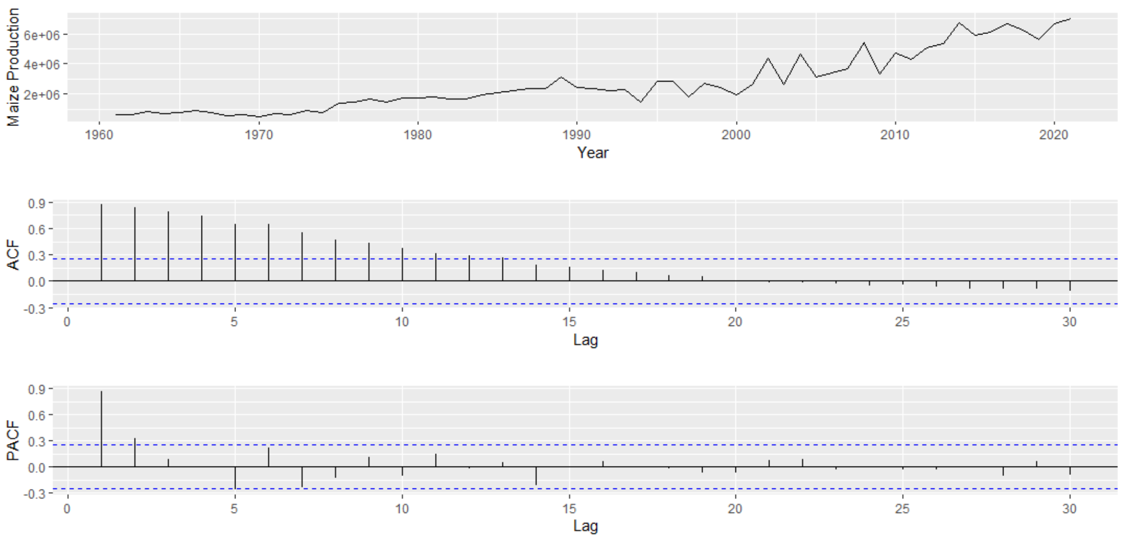

Figure 1. Time series, ACF and PACF plots

The stationarity of the data was tested using the ADF and KPSS tests. The results in Table 2 show that the data is not stationary. This affirms the positive trend shown by the time series plot and the show decay of the ACF plot.

Table 2. ADF and KPSS tests for raw data

ADF		KPSS	
statistic	*p*-value	statistic	*p*-value
-1.194	0.900	1.463	0.01

The data were first differenced and tested for stationarity. The time series, ACF and PACF plots of the differenced data in Figure 2 suggests that the differenced data are stationary. This can be seen from the rapid decay of the ACF and PACF plots, and also the fluctuation of the time series plot about a fixed point.

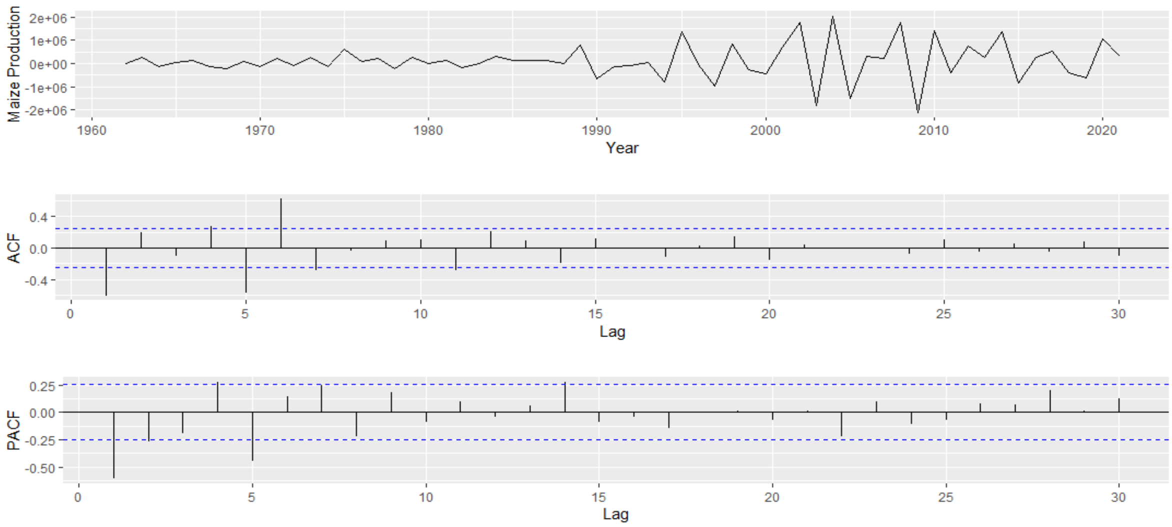

Figure 2. Time series, ACF and PACF plots of the differenced data

The stationarity of the differenced data is further affirmed by the use of the ADF and KPSS tests. The results in Table 3 revealed that the differenced data are stationary.

Table 3. ADF and KPSS tests of differenced data

ADF		KPSS	
statistic	*p*-value	statistic	*p*-value
-3.830	0.023	0.211	0.10

Using the ACF and PACF plots of the differenced data, fifteen (15) models were suggested for forecasting the maize production data in Tanzania. Table 4 presents the suggested models with their respective log-likelihood, AIC, AICc, and BIC values. From the results in Table 4, ARIMA(5,1,5) was identified as the best model among the competing models for forecasting maize production. It has the highest log-likelihood values and the smallest values for the AIC, AICc, and BIC. This means that forecasting with ARIMA(5,1,5) will provide a minimal loss of information compared to the other candidate models.

Table 4. Log-likelihood, AIC, AICc, and BIC of tentative models

Model	log-likelihood	AIC	AICc	BIC
ARIMA (0, 1, 1)	-887.42	1778.83	1779.05	1783.02
ARIMA (1, 1, 0)	-886.14	1776.27	1776.48	1780.46
ARIMA (1, 1, 1)	-885.14	1776.29	1776.72	1782.57
ARIMA (2, 1, 0)	-885.01	1776.01	1776.44	1782.29
ARIMA (2, 1, 1)	-884.97	1777.93	1778.66	1786.31
ARIMA (0, 1, 4)	-884.45	1778.90	1780.01	1789.37
ARIMA (1, 1, 4)	-874.55	1761.10	1762.68	1773.66
ARIMA (0, 1, 5)	-881.49	1774.98	1776.56	1787.54
ARIMA (1, 1, 5)	-874.30	1762.61	1764.76	1777.27
ARIMA (2, 1, 5)	-873.54	1763.08	1765.90	1779.83
ARIMA (4, 1, 5)	-868.82	1757.64	1762.13	1778.58
ARIMA (5, 1, 5)	-863.60*	1749.19*	1754.69*	1772.23*
ARIMA (4, 1, 0)	-879.98	1769.95	1771.06	1780.43
ARIMA (4, 1, 1)	-877.26	1766.51	1768.10	1779.08
ARIMA (4, 1, 4)	-869.17	1756.33	1759.93	1775.18

*: Means best based on the selection criterion

The parameters of the ARIMA(5,1,5) model were estimated and presented in Table 5. As shown in Table 5, except the θ_1 parameter all other parameters were significant at the 5% level of significance.

Table 5. Estimates of the parameters of ARIMA(5,1,5) model

Parameter	Estimate	Std. Error	z value	*p*-value
ϕ_1	-1.4148	0.1609	-8.7918	<0.0001*
ϕ_2	-0.5063	0.1414	-3.5817	0.0003*
ϕ_3	0.8543	0.0462	18.5061	<0.0001*
ϕ_4	1.4376	0.1460	9.8478	<0.0001*
ϕ_5	0.6274	0.1512	4.1485	<0.0001*
θ_1	1.2340	0.1717	7.1856	<0.0001*
θ_2	0.4185	0.2963	1.4123	0.1579
θ_3	-0.7617	0.2993	-2.5448	0.0109*
θ_4	-1.0624	0.2781	-3.8209	0.0001*
θ_5	-0.7847	0.1752	-4.4777	<0.0001*

*: Means significant at 5% level of significance

The ARIMA(5,1,5) model was further diagnosed to ensure that it is adequate for predicting future values of the maize production data. The diagnostic plots in Figure 3 revealed that the model is adequate. The standardized residuals display a stationary pattern, the ACF of the residuals shows insignificant autocorrelation and the *p*-values of the Ljung-Box statistics were all greater than 0.05 level of significance value.

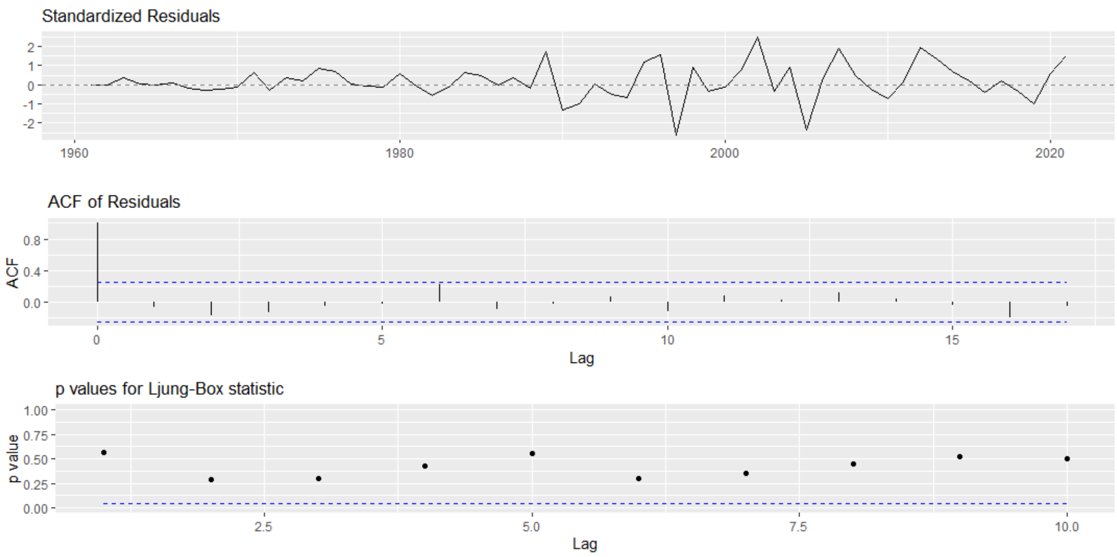

Figure 3. Model diagnostic plots

Since the diagnostic checks have revealed that the ARIMA(5,1,5) model is adequate for forecasting future values of the maize production data in Tanzania, ten (10) years of forecast of the production values were made using the model. The forecast values, 95% lower (LC) and upper (UP) confidence limits of the forecast values are presented in Table 6. The future production values of the maize production exhibit an intermittent pattern.

Table 6. Ten years forecast values for maize production

Year	Forecast	LC	UP
2022	6588463.78	5721615.90	7455311.66
2023	7483619.17	6373130.95	8594107.38
2024	7442284.50	6035463.29	8849105.72
2025	6919408.73	5292506.88	8546310.58
2026	7506434.94	5598093.32	9414776.56
2027	7909568.90	5923198.11	9895939.70
2028	7097466.86	4783908.94	9411024.78
2029	7766196.25	5347141.92	10185250.59
2030	8091534.14	5506632.81	10676435.46
2031	7546707.68	4816771.08	10276644.28

4. Conclusion

The study conducted a detailed analysis of maize production in Tanzania using the advanced Autoregressive Integrated Moving Average (ARIMA) model. After an analysis, it was determined that the production data showed stationarity once the initial differencing was done, confirming that the ARIMA model was to be used. Afterward, the model was adjusted to accurately reflect the underlying trends, yielding convincing findings that demonstrate its effectiveness in forecasting future maize output values in Tanzania.

The diagnostic assessments provided additional support for the model's predictive skills, confirming its strength in accurately predicting future patterns in maize output. A proactive strategy was employed, resulting in the creation of a ten-year projection that exposed a periodic production pattern expected to occur in the projected timeframe.

Therefore, suggestions were made, highlighting the urgent need for collaborative actions by the Tanzanian government and relevant stakeholders to strengthen maize production. One of the main ideas is to provide subsidies for necessary farm tools, to create a favorable environment for consistent output patterns. Stakeholders to make a real contribution to the resilience and productivity of maize cultivation in Tanzania by providing the required resources and support mechanisms. This will help strengthen the nation's food security and agricultural sustainability efforts.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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