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Original Research

A SARIMA Model for Forecasting Consumer Price Index in Tanzania

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Abstract

People must be well-informed on market swings in today's difficult economic times in order to cut excessive spending. Rising expenditures in a variety of sectors, including business, education, and healthcare can be burdensome for consumers, and accurate forecasting of household is necessary given the current technological innovation. The Consumer Price Index (CPI) is one of the statistical indicators used to estimate the changes in prices for commodities. Forecasting CPI can assist individuals in developing a plan for making decisions on their daily consumption. This study seeks to develop a SARIMA model for forecasting consumer price indices (CPI) in Tanzania by using data collected from International Monetary Fund (IMF) website from January 2010 to December 2022. Data were evaluated using time series methods such as time plots and stationarity tests. It was discovered that there is seasonality in the CPI index. However, a serial correlogram test was performed using a residual correlogram after which the variable was estimated using the SARIMA model and SARIMA (0, 1, 0) $(1, 1, 1)_{12}$ was fitted to the time series variable. The residual analysis was explored and because almost all correlations are zero, the SARIMA (1,1,1) $(0,1,2)_{12}$ model was appropriate for forecasting CPI index in Tanzania. Consumer price index was predicted for the next eighteen months and it has been observed that the trend of CPI is likely to increase in the next eighteen months.

Keywords: Correlogram, CPI, IMF.

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Introduction

Consumer Price Index (CPI) is an economic statistic that gives information on consumer-paid prices for goods and services. It is an instrument that is mostly used to measure inflation in the economy (Gjika Dhamo et al., 2018). The Consumer Price Index (CPI) provides an accurate measure of inflation that helps to estimate the purchasing power of the country given its currency and standard of living. (Zahara et al., 2020). The macroeconomic and fiscal policies of a government are greatly affected by the movement of the CPI, which also influences how the government adjusts expenditure and interest rates (Sibai et al., 2021). This has an impact on things like taxes and borrowing costs. For instance, the government may issue fewer social security checks when consumer price index falls and may raise interest rates in response to increase in CPI, thereby reducing borrowing costs and encouraging citizens to save more money rather than spending (Aparicio & Bertolotto, 2020). Consumer price index does not consider non-market activities, a broader quality of life issues, or the expenses and gains of the majority of government initiatives. Failure to use an inflation rate estimate may lead to inaccurate investment and saving decisions, which could eventually cause financial instability (Tang et al., 2019).

Failure to use an inflation rate estimate might lead to inaccurate investment and saving decisions, which could eventually cause economic instability (Zhao et al., 2020). Accurate CPI forecasting aids in decision-making for consumers and investors when it comes to spending and investment (Xu & Zhang, 2023). A job seeker who receives two offers that are comparable from companies in two separate regions may opt for the place with the lower CPI (Hadwan et al., 2022). It takes a lot of analysis of patterns and guesswork to anticipate the values of various variables, making forecasting a challenging task (Milunovich, 2020). The quality of the forecast is influenced by how accurate the data are used (Emong Herbert Robert & Mahmoud A. Abdel-Fattah, 2022). The choice of one forecasting approach over another may also be influenced by the accessibility of data (A et al., 2023).

Forecasting is important in the world of business when accurate forecasting results help the government to develop future policies (Corpin et al., 2023). Accurately predicting the change in the CPI is important for several economic variables, including efficiency, financial markets, and monetary policy (Wanto et al., 2018). Additionally, creating a reliable and accurate CPI forecasting model will be extremely important for the general public, decision-makers, and academics (Rohmah et al., 2021). Due to its importance in the economy, CPI prediction has attracted the interest of numerous scholars in recent years. The primary objective of this article is to develop SARIMA model for predicting consumer price index in Tanzania.

Statement of the problem

People must be well-informed on market swings in today's difficult economic times in order to cut excessive spending (Fahrudin & Sumitra, 2019). Rising expenditure in a variety of sectors, including business, education, and healthcare, can be burdensome for consumers thus, accurate forecasting of household expenses requires technological innovation (Wanjuki et al., 2022). Modelling and forecasting can assist individuals in developing a plan for making decisions on their daily consumption (S.-Y. Zhang et al., 2023).

Although many studies have used the ARIMA model to analyze and predict CPI with rather outstanding results, the author contends that the CPI as an economic cycle indicator contains obvious seasonal characteristics. The seasonal autoregressive moving average model (SARIMA) should be used since it can more closely match the CPI trend characteristics. Therefore, this study used monthly data from Tanzania to establish a SARIMA model for empirical analysis and forecasting, this will provide a definite reference for the decision-making of various market organizations, such as business entities.

Literature Review

Numerous studies have been carried out for CPI forecast analysis. However, an ideal model for consumer price index prediction has not yet been agreed upon by researchers.

In order to forecast the consumer price index (CPI), Konarasinghe (2022) looked for the optimal time series model. The International Monetary Fund (IMF) database was used to obtain monthly CPI figures for Thailand for the time period from May 2012 to October 2021. To predict CPI in Thailand, models like ARIMA, Holt's technique, and Auto-Regressive Distributed Lag Model (ARDLM) were tested. The model assumptions were examined using the Auto Correlation Function (ACF), Anderson Darling test, and Ljung-Box Q (LBQ) test. The capacity of the model to predict the future was evaluated using relative and absolute techniques in measurements of errors. The findings of the study showed that the ARDLM with lags 1 and 2 is the best model for predicting Thailand's CPI.

Time series data from January 2015 to December 2017 were used by Costales (2021) to study the Consumer Price Index of the Philippines. The researchers determined that SARIMA (1,1,0) $(1,0,0)_{12}$ is the best mathematical model for predicting future CPI values based on the AIC as criteria in selecting the best model.

In order to assess the potential ARIMA models' predictive power in Nigeria price index data, Ibrahim et al. (2023) used monthly data from January 2010 to August 2022 form the national Bureau of Statistics to examine the predictive ability of the possible ARIMA models. Based on the study ARIMA (1,2,0) from among the competing models was found to be effective for generating CPI forecasts.

Uwilingiyimana et al. (2015) used the ARIMA and GARCH models for conducting an inflation study in Kenya by using 180 monthly data values. The results demonstrated that, in comparison to GARCH (1,2) model, the ARIMA (1, 1, 12) model was able to create forecasts based on stationarity test and history patterns in the data. He went on to demonstrate that the model, when compared to earlier forecasting techniques, produced the best results and significantly increased estimation and forecasting accuracy.

In the case of Tanzania, Nyoni (2019) used ARIMA to forecast the inflationary trend. He discovered that the ARIMA models (1, 1, 2) had a better forecasting accuracy. According to Ngailo et al. (2014) who studied inflation using time series models with

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data from January 1997 to December 2010, the GARCH (1, 1) model is the best fit and most useful for forecasting inflation in Tanzania.

Methodology

The main objective of this research is to establish a SARIMA model for forecasting consumer price index in Tanzania. Forecasting is potential because it helps investors and the government in the energy sector to make informed decisions. Monthly CPI data from International monetary fund (IMF) website from January 2000 to February 2022 were analyzed by using R software in order to obtain the optimal model. The following sections provide a comprehensive description of each technique used.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Models

SARIMA is an extension of the ARIMA model that fits seasonal time series data. Seasonality is defined as a consistent pattern of recurring movements throughout time in a given time series (Wanjuki et al., 2022). Most time-series data exhibit seasonality, rendering the ARIMA model inefficient in forecasting a specific series (Majhi et al., 2023). The seasonal ARIMA (SARIMA) model combines the Autoregressive and Moving Average terms in an ARIMA model that forecasts the given time series using historical values and noises, with lags (h) representing the series' periodicity. ARIMA (p, d, q) denotes the nonseasonal ARIMA part, where p is the order of the AR part, d is the order of differencing to keep data stationary, and q is the order of the MA part. As a result, the SARIMA model, which combines non-seasonal and seasonal components in a model, is abbreviated as ARIMA (p, d, q) (P, D, Q)h, where h denotes the number of seasons or the time span of the recurrent seasonal pattern (Mustapha et al., 2021).

$$\phi(\mathrm{B}^{\mathrm{h}})\varphi(\mathrm{B})(1-B^{s})^{D}(1-B)^{d}\mathrm{X}_{\mathrm{t}} - \mu = \theta(\mathrm{B}^{\mathrm{m}})\Theta(\mathrm{B})\varepsilon_{\mathrm{t}} \quad (1)$$

Where in (1), $\phi(\mathrm{B}^{\mathrm{h}})$ is the seasonal AR process, $\varphi(\mathrm{B})$ is the non-seasonal AR process, $\theta(\mathrm{B}^{\mathrm{m}})$ is the seasonal MA process, $\Theta(\mathrm{B})$ is the non-seasonal MA process, X_{t} is actual observation at time t, B is the backshift operator, ε_{t} is white noise, μ is the constant and h is the seasonal component's periodicity. The processes can be written using the backward shift operator as shown in (2), (3), (4) and (5):

$$\phi(B^{h}) = 1 - \phi_1 B^{h} - \phi_2 B^{2h} - \phi_3 B^{3h} - \cdots - \phi_{\mathrm{p}} B^{\mathrm{ph}} \quad (2)$$

$$\varphi(\mathrm{B})\mathrm{X}_{\mathrm{t}} = 1 - \varphi_1 \mathrm{X}_{\mathrm{t-1}} - \varphi_2 \mathrm{X}_{\mathrm{t-2}} - \varphi_3 \mathrm{X}_{\mathrm{t-3}} - \ldots - \varphi_{\mathrm{p}} \mathrm{X}_{\mathrm{t-p}} \quad (3)$$

$$\theta(\mathrm{B}^{\mathrm{m}}) = 1 - \theta_1 B^{\mathrm{m}} - \theta_2 B^{2\mathrm{m}} - \theta_3 B^{3\mathrm{m}} - \ldots - \theta_{\mathrm{q}} B^{\mathrm{qm}} \quad (4)$$

$$\Theta(B)\varepsilon_t = 1 - \Theta_1\varepsilon_{t-1} - \Theta_2\varepsilon_{t-2} - \Theta_3\varepsilon_{t-3} - \dots - \Theta_q\varepsilon_{t-q} \quad (5)$$

Stationarity

Data must be examined for stationarity in time series analysis. A time series is said to be stationary if its mean and variance remain constant (Uwilingiyimana et al., 2015). A time plot or the Augmented Dickey Fuller (ADF) test can be used to test for stationarity. If the time series is proven to be stationary, the statistical properties will be the same in the future as they were in the past (Gjika Dhamo et al., 2018). The stationarity requirement ensures that the estimated model's autoregressive parameters remain constant within a defined range and that the moving average parameters are invertible. If this criterion is met, the estimated model can be used for forecasting (Fahrudin & Sumitra, 2019). To test for the unit root in the series, this study employs the Augmented Dickey-Fuller (ADF) test.

Box Jenkins Methodology

The Box Jenkins methodology approach was used in this study to carry out the modeling procedure which includes the stages of model identification, model specification, model estimation, and model diagnostics, as well as preliminary steps of checking for data stationarity and general model class specification (Rapoo et al., 2022). It involves the following steps

Model Identification and selection

Given that commodity prices are likely to exhibit a seasonal component as a result of seasonality in production or supply chains, the current study hypothesizes that the SARIMA model best fits the data under discussion. The SARIMA model is intended for time series with seasonality. It combines non-seasonal and seasonal components in the model and is denoted as ARIMA (p, d, q) $(P, D, Q)_h$, therefore selecting or specifying the appropriate model is critical as illustrated below.

Model selection involves selecting the model that best fits the available data. The principle of parsimony states that the model with the fewest parameters is preferred and employed. The first and most crucial step in modeling is determining the best order for the SARIMA (p, d, q) (P, D, Q) model (Koula et al., 2020). Orders p and q are determined by graphing ACF and PACF at different lag lengths whereas d is determined by the Integration (1) or Integration (0) approach (Divisekara et al., 2021). These two plots highlight the type of model we should develop.

Model Estimation

Following the identification of the model, the second stage in SARIMA model construction is the estimation of selected model parameters. The parameters were estimated using the maximum likelihood estimation (MLE) approach. Because the previous lagged observations of noise terms cannot be detected in a SARIMA framework,

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the MLE technique is adopted over Ordinary Least Squares (OLS) regression analysis due to its efficiency (Boniface & Martin, 2019).

Model Diagnostic

After estimating the parameters of the model, the next phase in Box-Jenkin's methodology is to assess the model's adequacy also known as model diagnostics. A model should be able to extract all systematic properties from data. The residuals (the percentage of the data not explained by the model) should be small. As a result, the diagnostic check is based on the residuals of the model. One notion is that the residuals of an acceptable model should be white noise. The residuals are known as Gaussian White Noise if they are normally distributed with a mean of zero and a constant variance (Dum & Essi, 2017).

Autocorrelation is another diagnostic test used in this study. A correlogram can be used to test the autocorrelation in the residuals. If there is no serial connection, autocorrelations and partial autocorrelations should be near to zero at all lags. To establish serial independence, a statistical method such as the Ljung Box Q statistic can be utilized. The Box-Pierce Q and Ljung-Box LB statistics were utilized in this study to determine the presence of serial correlations in the residuals (Magnus Ogolo & Lekia, 2022). The Box-Pierce Q statistics is denoted by (6).

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{{e_k}^2}{n-2} \tag{6}$$

Where in (6) e_k indicates the residual autocorrelation at a given lag k, n is the number of residuals, and m the number of time lags. All Q-Statistics should be insignificant if there is no serial correlation between residuals (Chhorn & Chaiboonsri, 2018). Normality and homoscedasticity of residuals were tested by using statistical tools such as the Autoregressive Conditional Heteroskedastic Lagrange multiplier (ARCH-LM) (Gjika Dhamo et al., 2018).

Results and Discussion

Stationarity of the data

Figure 1 displays the plot of historical CPI index data from January 2000 to December 2022. The series shows an overall upward trend, given the seasonal component of the series, the SARIMA model is appropriate because it captures seasonality that exits in the series.

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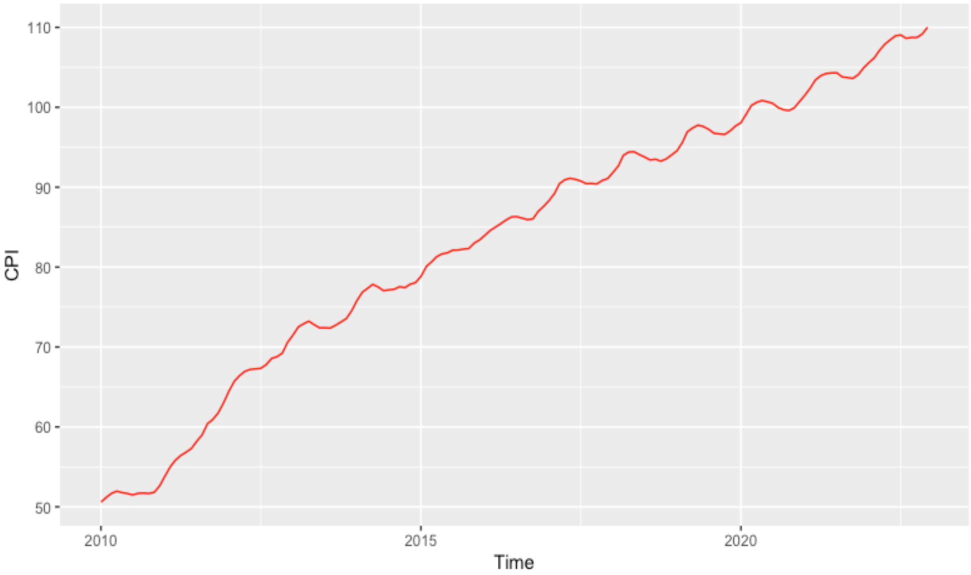

Figure 1. The trend of consumer price index

The Augmented Dickey-Fuller (Dickey-Fuller = -2.149, p-value = 0.5142) unit roots test revealed that the series was not stationary at level. The series became stationary after the first differencing and seasonal differencing at lag 12. The ADF test was applied to confirm whether the time series was stationary (Dickey-Fuller = -3.8388, p-value = 0.01914). Based on the results, D=1 in the seasonal ARIMA (P, D, Q) model and d=1 in non-seasonal ARIMA (p, d, q) case.

Model identification and selection

The order of the best fit can be chosen using the ACF and PACF, however it is not always accurate enough. In order to get the most efficient model from a combination of different orders having seasonal and non-seasonal parts, a grid search of feasible orders was use.

Table 1: SARIMA models using AIC

S/N	SARIMA MODEL	AIC
1	SARIMA (0,1,0) $(0,1,0)_{12}$	93.94685
2	SARIMA (1,1,0) $(1,1,0)_{12}$	36.58713
3	SARIMA (0,1,1) $(0,1,1)_{12}$	47.36842
4	SARIMA (1,1,0) $(0,1,0)_{12}$	39.20056
5	SARIMA (1,1,0) $(2,1,0)_{12}$	28.12904
6	SARIMA (1,1,0) $(2,1,1)_{12}$	25.50199
7	SARIMA (1,1,0) $(2,1,2)_{12}$	27.26475
8	SARIMA (1,1,0) $(1,1,2)_{12}$	25.16021
9	SARIMA (1,1,0) $(0,1,2)_{12}$	23.50938
10	SARIMA (1,1,0) $(0,1,1)_{12}$	30.97651

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S/N	SARIMA MODEL	AIC
11	SARIMA (0,1,0) $(0,1,2)_{12}$	72.39362
12	SARIMA (2,1,0) $(0,1,2)_{12}$	22.362
13	SARIMA (2,1,0) $(0,1,1)_{12}$	30.2588
14	SARIMA (2,1,0) $(1,1,2)_{12}$	24.20429
15	SARIMA (3,1,0) $(0,1,2)_{12}$	24.24369
16	SARIMA (2,1,1) $(0,1,2)_{12}$	24.10126
17	SARIMA (1,1,1) $(0,1,2)_{12}$	21.94772
18	SARIMA (1,1,1) $(0,1,1)_{12}$	30.0387
19	SARIMA (1,1,1) $(1,1,2)_{12}$	23.82919
20	SARIMA (0,1,1) $(0,1,2)_{12}$	40.52604
21	SARIMA (1,1,2) $(0,1,2)_{12}$	24.10491
22	SARIMA (0,1,2) $(0,1,2)_{12}$	31.53773
23	SARIMA (2,1,2) $(0,1,2)_{12}$	26.31055

The minimum AIC served as the basis for choosing the appropriate order of the best fit model. From table 1, SARIMA (1,1,1) (0,1,2)12 (AIC=21.94772) was the best model out of the 23 competing models.

Model Estimation

The model coefficients were estimated using the Maximum Likelihood Estimation method. The SARIMA (1,1,1) (0,1,2)12 comprises a non-seasonal AR process, a seasonal AR process, a non-seasonal MA process, two seasonal MA processes, a non-seasonal difference (d = 1), and a seasonal difference (D = 1). The fitted model's parameter estimates were; $\varphi_1 = 0.7557,\ \Theta = -0.3004,\ \theta_1 = -0.2933,\ \theta_2 = -0.3013$. The mathematical equation of the resulting SARIMA (1,1,1) (0,1,2)12 model is given by (7)

$$(1 - 0.7557B)(1 - B^{12})(1 - \mathrm{B})\mathrm{X_t} = (1 + 0.3004B)(1 + 0.2933B^s + 0.3013B^{2s})\varepsilon_{\mathrm{t}} \quad (7)$$

Model Diagnostic Check

Diagnostic tests were carried out in this study, specifically to determine whether the residuals of the fitted model adhered to the assumptions of normality and autocorrelation. The model residuals need to be in independent and identically distributed with a constant mean and variance. There should not be autocorrelation between the residuals.

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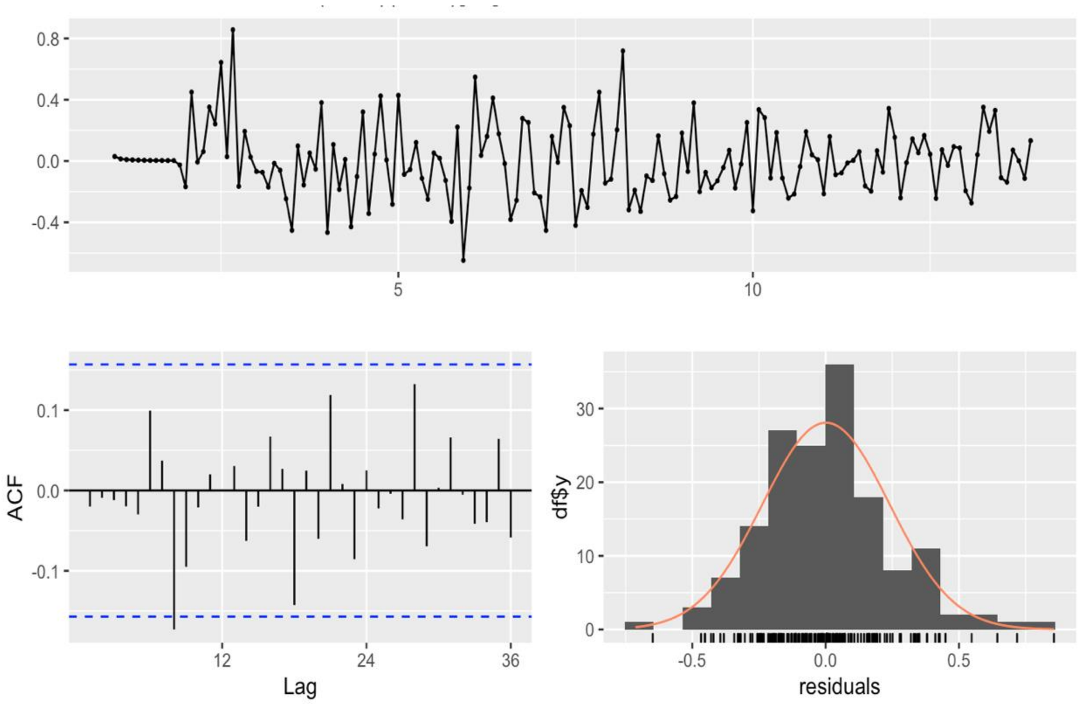

Figure 2. Residual plots

The normal curve in figure 2 indicates that the residuals have an approximately normal distribution. In addition, there is inadequate support for any significant spikes in the ACF plot as presented in figure 2. Thus, the autocorrelation between residuals is not significant. The Ljung-Box Q-test which displays Q-statistics (all $p > 0.05$) supports the conclusion. Furthermore, result indicates that fitting the ARCH model is unnecessary because residuals are only white noise, and the fitted SARIMA (1,1,1) (0,1,2)12 model can be used instead for forecasting.

Model prediction

Since forecasting provides an insight about the future variability, it aids in planning and decision-making. The CPI for the upcoming 18 months is predicted and examined using the SARIMA (1,1,1) (0,1,2)12 model. Table 2 displays specific data from predictive analysis and Figure 3 displays expected CPI index. The forecast shows that CPI has been rising over time and is probably going to continue to do so. The study's findings are in line with those of earlier research done by Lidiema (2017), Muthu et al., (2021), X. Zhang (2023) and Naden & Etuk (2017).

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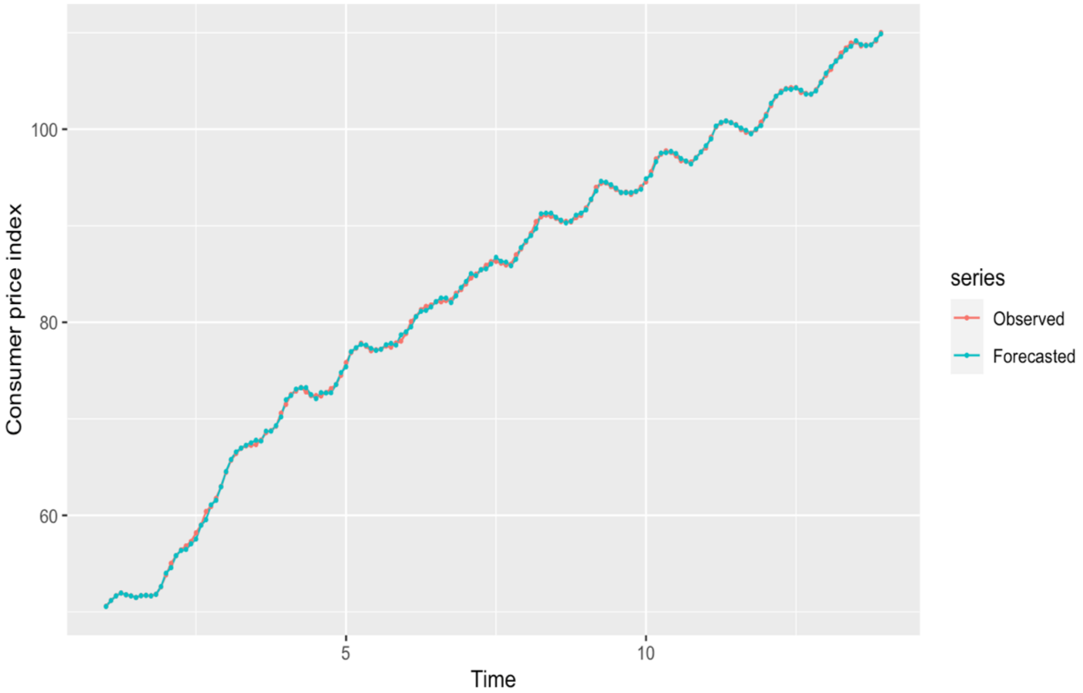

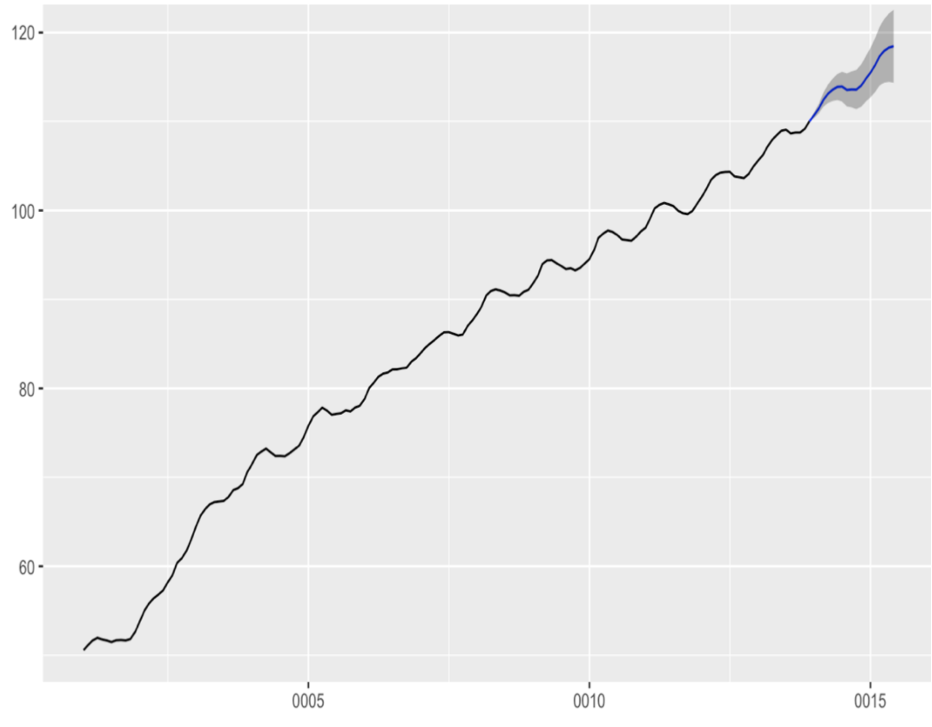

Figure 3. Observed Vs Forecasted

Table 2. CPI forecast for the next 18 months

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2023	110.6967	110.3795	111.0139	110.2115	111.1819
Feb 2023	111.4691	110.9090	112.0293	110.6124	112.3258
Mar 2023	112.4272	111.6274	113.2270	111.2040	113.6503
Apr 2023	113.1249	112.0922	114.1576	111.5455	114.7043
May 2023	113.5665	112.3100	114.8230	111.6449	115.4881
Jun 2023	113.8770	112.4071	115.3469	111.6290	116.1250
Jul 2023	113.9091	112.2364	115.5819	111.3509	116.4674
Aug 2023	113.5312	111.6659	115.3964	110.6785	116.3838
Sep 2023	113.5859	111.5378	115.6339	110.4537	116.7180
Oct 2023	113.5728	111.3511	115.7944	110.1750	116.9705
Nov 2023	113.9955	111.6086	116.3824	110.3451	117.6459
Dec 2023	114.7740	112.2296	117.3185	110.8827	118.6654
Jan 2024	115.4848	112.7078	118.2617	111.2378	119.7317
Feb 2024	116.3403	113.3075	119.3732	111.7020	120.9787
Mar 2024	117.3240	114.0242	120.6239	112.2774	122.3707
Apr 2024	117.9392	114.3695	121.5089	112.4799	123.3985
May 2024	118.2921	114.4549	122.1292	112.4236	124.1605
Jun 2024	118.4535	114.3541	122.5529	112.1840	124.7230

Conclusion and Recommendation

Conclusion

Central banks design and implement monetary policy such as interest rate setting and price controls based on the future course of market prices. As a result, forecasting models have become popular in policy development. This study applied Box-Jenkins methodology to develop a predictive SARIMA model for monthly CPI data in Tanzania from January 2000 to December 2022. The results revealed that SARIMA (1,1,1) $(0,1,2)_{12}$ (AIC = 21.94772) was the best in the class of 23 competing SARIMA models.

Recommendation and Areas for further studies

Because the Consumer Price Index (CPI) keeps increasing, the government should use fiscal tools such as interest rate caps, reduced government spending, and sustainable taxes to control inflation.

Future research may look into hybrid models like SARIMA and machine learning techniques such as Support Vector Regressor (SVR) and Random Forest Regressor (RFR) that incorporate covariates to improve the prediction of consumer price index. To account for additional volatility in commodity prices, the SVR model incorporate consumer price index predictors such as interest rates and taxes.

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