

Monthly Inflation Dynamics in Somalia Using Seasonal ARIMA Models

Abdirashiid mohamud mohamed

B9EC1053@st.snu.edu.so

Somali National University

Research Article

Keywords: SARIMA, Inflation forecasting, Somalia, Seasonal price cycles, Box–Jenkins, CPI, Developing economies

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10675884/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Monthly Inflation Dynamics in Somalia Using Seasonal ARIMA Models

Abdirashiid Mohamud Mohamed

Corresponding author

B9EC1053@st.snu.edu.so

ORCID iD: <https://orcid.org/0009-0009-3736-2164>

Abstract

Accurate short-term inflation forecasting is essential for macroeconomic surveillance and evidence-based policy planning, yet empirical research on Somalia's price dynamics remains scarce and methodologically limited. This study applies a Seasonal Autoregressive Integrated Moving Average (SARIMA) framework to model and forecast Somalia's monthly Consumer Price Index (CPI)-derived inflation rate over the period February 2018 to December 2024, using data from the Somalia National Bureau of Statistics (SNBS). To the best of the author's knowledge, this is the first study within the Somali-territory literature to apply a seasonal time-series framework directly to a CPI-derived monthly inflation rate series, addressing a consistent methodological gap in prior work. Following the Box–Jenkins procedure, Augmented Dickey–Fuller and Phillips–Perron unit-root tests confirm stationarity at level, $I(0)$, requiring no differencing transformation. Autocorrelation and partial autocorrelation analysis reveal a dominant annual seasonal structure at lag 12 alongside moderate short-run persistence. Among nine candidate specifications, SARIMA $(1,0,0)(1,0,0)_{12}$ is selected as the optimal model on the basis of Akaike and Bayesian information criteria and Portmanteau residual diagnostics. The estimated seasonal AR (12) coefficient of 0.8274 is positive, large in magnitude, and statistically significant at the 1% level, confirming that annual seasonal recurrence is the primary driver of Somalia's monthly inflation dynamics. Hold-out evaluation for 2024 yields a Mean Absolute Error of 0.2909 percentage points and a Root Mean Squared Error of 0.3399 percentage points — approximately 28% and 33% of the series unconditional standard deviation respectively — confirming strong short-term predictive performance. Rolling-window estimation further establishes that the seasonal parameter remained structurally stable throughout the post-sample period. Out-of-sample forecasts for 2025–2026 project recurring March–May inflation peaks, consistent with post-deyr food supply adjustments and Ramadan-related demand pressures, alongside deflationary episodes in January, August, and December. These findings provide a statistically rigorous and institutionally grounded baseline for seasonal inflation monitoring, fiscal planning, and social protection programming in Somalia.

Keywords: SARIMA; Inflation forecasting; Somalia; Seasonal price cycles; Box–Jenkins; CPI; Developing economies.

1. Introduction

Inflation, broadly defined as a sustained increase in the general price level of goods and services over time, represents one of the most consequential macroeconomic challenges facing both policymakers and households. By eroding the purchasing power of money, inflation reduces real incomes, weakens household welfare, discourages productive investment, distorts resource allocation, widens income inequality, and may intensify financial instability, particularly in economies where low-income households devote a large share of expenditure to essential goods and services (Boniface & Martin, 2019; Chavez Hurtado & Cortes-

Fregoso, 2013; Mehdiyev & Enke, 2014). Given its central role in macroeconomic performance and its direct implications for monetary, fiscal, and social policy, accurate short-term inflation forecasting is an essential input into evidence-based economic governance (McAdam & McNelis, 2005; Otu et al., 2014).

The Consumer Price Index (CPI) is the most widely used empirical measure for tracking inflation, as it captures changes in the average price level of a representative basket of goods and services consumed by households. CPI-based inflation indicators support a broad range of policy decisions, including wage adjustment, budget preparation, savings and investment planning, and social protection targeting (Purbasari et al., 2020; Imron et al., 2022; Kamagaté et al., 2025). Consequently, the development of reliable CPI-based inflation forecasting frameworks is particularly important in economies where price movements are volatile, statistical infrastructure is still developing, and policy space is constrained.

Somalia represents such a context. The country's inflation dynamics are shaped by structural vulnerability to external price shocks, heavy dependence on imported essential commodities, reliance on diesel-powered electricity generation, exposure to global energy-price fluctuations, recurrent climate-induced supply disruptions, and limited real-time market monitoring capacity. Recent post-sample institutional evidence from the Somalia National Bureau of Statistics further shows that these vulnerabilities remain highly relevant. Mohamed (2026) reports that annual inflation reached 5.1% in 2025, with particularly strong price pressures in restaurants and accommodation, personal care goods, health, and food and beverages. The same policy brief also documents that the escalation of the Iran conflict in late February 2026 was followed by a sharp domestic fuel-price increase in Mogadishu, from approximately US\$0.60 to US\$1.50 per litre, transmitting cost-push inflation through transport, food distribution, utilities, and imported consumer goods. Although this 2026 episode lies outside the estimation sample of the present study, it provides important post-sample policy context and illustrates why Somalia requires systematic inflation forecasting combined with real-time market surveillance.

The Somalia National Bureau of Statistics is the official institution responsible for collecting and disseminating CPI data in Somalia. Through its monthly CPI reports, SNBS tracks price changes across major expenditure categories, including food and non-alcoholic beverages, clothing and footwear, housing, electricity and fuel, health, transport, communication, and education. The monthly frequency of the CPI series makes it suitable for empirical time-series analysis and short-term inflation forecasting. In the present study, the CPI level series is transformed into a month-on-month inflation rate in order to model the actual rate of price change rather than the level of the price index.

Against this background, the present study pursues three specific objectives: first, to examine the statistical properties and seasonal dynamics of Somalia's monthly CPI-derived inflation series over the period February 2018 to December 2024; second, to identify and estimate an optimal Seasonal Autoregressive Integrated Moving Average model that best characterizes the observed inflation dynamics; and third, to generate short-term out-of-sample inflation forecasts that can inform macroeconomic surveillance, budget preparation, wage adjustment, and social protection planning. The SARIMA framework is selected because it explicitly accommodates both non-seasonal and seasonal autocorrelation structures in monthly time-series data, making it appropriate for inflation series that exhibit recurring intra-year price fluctuations. It is also suitable for data-constrained developing-economy contexts where more complex multivariate or machine-learning models may require longer and richer datasets.

Although inflation forecasting has received substantial attention in the wider empirical literature, studies focusing specifically on Somalia remain scarce and methodologically limited. Existing Somali-territory studies have generally applied ARIMA-type models directly to CPI level data rather than to CPI-derived monthly inflation rates, a specification that may obscure the short-run rate of price change and the seasonal fluctuations embedded within it (Mohamed, 2020; Hussein & Abdillahi, 2025). To address this gap, the

present study transforms monthly CPI data into a month-on-month inflation rate and applies a SARIMA framework capable of jointly modelling non-seasonal and seasonal dynamics. In doing so, the study provides a more granular, empirically rigorous, and policy-relevant characterization of Somalia's inflation process.

The remainder of the paper is organized as follows. Section 2 reviews the relevant empirical and methodological literature. Section 3 presents the data and modelling framework. Section 4 reports and discusses the empirical results and forecasting performance. Section 5 concludes with policy implications, limitations, and directions for future research.

2. Literature Review

The empirical literature on inflation forecasting has expanded considerably over recent decades, driven by both the macroeconomic significance of price stability and sustained advances in quantitative modelling techniques. Three broad methodological strands can be identified: classical univariate time-series models, principally Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension (SARIMA); hybrid approaches that augment ARIMA with Generalised Autoregressive Conditional Heteroscedasticity (GARCH) specifications to accommodate time varying volatility; and machine learning and decomposition methods, including Artificial Neural Networks (ANN) and Seasonal and Trend decomposition using Loess (STL). The choice among these approaches is not arbitrary but is conditioned by data frequency and sample length, the regularity and amplitude of seasonal price patterns, institutional data availability, and the intended forecasting horizon. In contexts characterised by short monthly time series, limited institutional data infrastructure, and pronounced intra-year price variability — conditions that broadly define fragile and developing economies — univariate seasonal models have consistently demonstrated competitive forecasting performance relative to more data-intensive alternatives.

SARIMA and Univariate Seasonal Models

Among classical univariate approaches, the SARIMA framework has been widely and successfully applied to monthly CPI and inflation series across developing economies, consistently yielding reliable short-term forecasts. Mwanga (2020) applied SARIMA to Uganda's monthly CPI data spanning January 2010 to July 2020, identifying SARIMA(1,1,1)(0,1,1)₁₂ as the optimal specification on the basis of AIC and BIC criteria, with projected inflation rates ranging between 4.7% and 6.0% over the subsequent twelve months. Otu et al. (2014) similarly employed SARIMA modelling to forecast monthly inflation in Nigeria over the period November 2003 to October 2013, selecting SARIMA(1,1,1)(0,0,1)₁₂ as the best-fitting model. More recently, Kamagaté et al. (2025) extended the SARIMA framework to Côte d'Ivoire's monthly CPI, identifying SARIMA(0,1,0)(0,1,1)₁₂ as the most appropriate linear specification and demonstrating that the incorporation of a GARCH(1,0) component to address residual heteroscedasticity yielded further improvements in forecast accuracy. Collectively, these studies establish that SARIMA models are capable of capturing both non-seasonal serial dynamics and the recurring intra-year fluctuations that characterise inflation in developing-economy contexts, providing strong methodological support for the framework adopted in the present study.

Non-Seasonal ARIMA and the Somali-Territory Literature

A related strand applies non-seasonal ARIMA models to CPI or inflation data, typically using annual or aggregated series where seasonal variation is less pronounced. Poudel et al. (2024) applied the Box–Jenkins procedure to Nepal's annual National Consumer Price Index over the period 1972/73 to 2022/23, identifying ARIMA(1,2,8) as the best-fitting specification and projecting a continued upward price trajectory. Rizwan et al. (2025) similarly employed ARIMA to forecast medium-term CPI inflation in Pakistan using annual

data from 2002 to 2023, projecting a gradual moderation in inflation consistent with monetary policy tightening. In a closely related contribution, Maiga (2024) investigated Tanzania's annual inflation rate over the period 1990 to 2021 using World Bank data, applying the Box–Jenkins procedure with ADF and PP unit-root tests to confirm non-stationarity before differencing. Among candidate specifications, ARIMA(1,1,1) was selected as the optimal model on the basis of diagnostic checks, with the study noting that the absence of pronounced seasonality rendered SARIMA modelling unnecessary for annual data. The study contributes evidence that ARIMA frameworks can adequately characterise inflation dynamics in Sub-Saharan African economies when seasonal variation is not a dominant feature of the data-generating process. Within the Somali context specifically, Mohamed (2020) compared ARIMA and regression models with ARIMA errors to forecast Somaliland's CPI using monthly data from 2013 to 2020, identifying ARIMA(0,1,3) as the most appropriate specification. Hussein & Abdillahi (2025) applied ARIMA to Somalia's monthly CPI data over the period November 2022 to November 2024, identifying ARIMA(1,1,0) as the optimal model and projecting a relatively stable CPI over the forecast horizon. While these two studies differ in territorial scope and data coverage Mohamed (2020) focusing on Somaliland over a seven-year period and Hussein & Abdillahi (2025) covering Somalia over a shorter two-year window their shared application of ARIMA to CPI level data rather than CPI-derived inflation rate series constitutes a consistent methodological limitation across the broader Somali context. Modelling the CPI level rather than the month-on-month inflation rate precludes identification of the actual rate of price change and the seasonal fluctuations embedded within it limitations that the SARIMA framework applied in the present study explicitly addresses. The most current institutional evidence on Somalia's inflation dynamics is provided by Mohamed (2026), whose SNBS policy brief documents the rapid and severe transmission of the February 2026 global oil shock into domestic prices through fuel costs, transport fares, maritime shipping insurance premiums, and imported food prices. Annual inflation had already reached 5.1% by December 2025, with particularly acute sectoral pressures in restaurants and accommodation (+14.1%), personal care goods (+11.0%), and health (+10.6%), driven by drought-related supply constraints and rising import costs. Critically, this evidence confirms that Somalia's inflation dynamics are shaped by both recurring seasonal patterns including post-deyr food supply adjustments and Ramadan-related demand surges — and acute exogenous structural breaks driven by geopolitical events, underscoring that a seasonal time-series framework capable of capturing intra-year periodicity provides the most appropriate baseline forecasting tool for this economy, while simultaneously highlighting the limitations of univariate approaches when confronted with sudden regime shifts. Hybrid ARIMA–GARCH Approaches A further strand of the literature investigates hybrid ARIMA–GARCH specifications, motivated by evidence that inflation series frequently exhibit conditional heteroscedasticity time-varying volatility clusters that standard linear ARIMA models are structurally unable to capture. Qasim et al. (2021) analysed Pakistan's monthly CPI inflation from January 1962 to December 2019, finding that an ARIMA–GARCH framework outperformed asymmetric GARCH alternatives, with GARCH(2,2) identified as the most appropriate variance specification. Kustiara et al. (2020) applied a comparable hybrid approach to sectoral CPI data in East Java, Indonesia, identifying ARIMA(2,2,2)–GARCH(1,0) as the optimal specification and confirming enhanced forecasting reliability through improved residual diagnostics. Kurniasari et al. (2023) further compared ARIMA–GARCH and ANN models using Indonesian CPI data from January 2006 to December 2021, finding that while ARIMA(4,2,2)–GARCH(1,1) achieved a MAPE of 3.19%, an ANN model with two hidden layers outperformed it with a MAPE of 1.24%. Although hybrid specifications demonstrate superior accuracy in certain settings, their performance gains are predominantly realised over long, structurally stable data series conditions that do not characterise Somalia's relatively short and volatile CPI record, rendering their direct application to the present context methodologically inappropriate.

Machine Learning and Decomposition Methods

Beyond classical and hybrid time-series approaches, a growing body of literature explores machine learning and decomposition techniques for inflation forecasting, with mixed conclusions regarding their superiority over classical alternatives. Chavez Hurtado and Cortes-Fregoso (2013) applied ANN models to

Mexico's inflation rate, finding that neural network architectures generated accurate forecasts across volatile, transitional, and stable inflation regimes, outperforming official central bank projections. In a Horn of Africa context directly relevant to the present study, Ali and Mohamed (2022) compared multiple forecasting models for Puntland's CPI using monthly data from July 2017 to February 2021, finding that ANN and STL decomposition models outperformed classical alternatives on AIC, AICc, and BIC criteria. Sultana (2013), however, compared decomposition and ARIMA methods for Pakistan's CPI using monthly data from July 2008 to June 2013 and found that forecasting accuracy varied across methods and variables a result that cautions against assuming any single approach is universally superior and underscores the context dependence of method selection. Işığçok et al. (2022) similarly found that ARIMA and ANN models produced comparably accurate forecasts for Turkish CPI data from January 2002 to March 2019, suggesting that the relative advantage of machine learning methods is neither consistent nor generalisable. Taken together, these findings must be interpreted with caution: machine learning and decomposition models typically require substantially larger training samples to generalise reliably out-of-sample, and their outputs offer limited interpretability for policy communication a consideration of particular relevance in institutional contexts with nascent statistical capacity such as Somalia.

Synthesis and Research Gap

The reviewed literature yields three methodological conclusions that directly motivate the present study. First, SARIMA models have demonstrated consistent and reliable short-term forecasting performance for monthly CPI and inflation series across diverse developing-economy contexts, particularly where data samples are moderate in length and intra-year seasonal price dynamics are evident (Mwanga, 2020; Otu et al., 2014; Kamagaté et al., 2025). This conclusion resonates with foundational evidence from advanced-economy contexts: Stock & Watson (2006), examining U.S. Federal Reserve inflation forecasting, found that the univariate inflation process is well described by an unobserved-component trend-cycle model with stochastic volatility, equivalent to an integrated moving average process with time-varying parameters, and that multivariate models consistently failed to outperform this well-specified univariate benchmark. If multivariate forecasts struggle to improve on univariate models even in a data-rich, institutionally advanced economy, the case for parsimonious univariate approaches such as SARIMA is considerably strengthened in data-constrained developing-economy contexts. Second, while hybrid ARIMA–GARCH, machine learning, and decomposition approaches offer accuracy gains under specific conditions, their data requirements, computational complexity, context-dependency, and limited policy interpretability constrain their applicability in fragile institutional environments characterised by short data histories and limited analytical capacity (Qasim et al., 2021; Kurniasari et al., 2023; Sultana, 2013; Işığçok et al., 2022). Third, and most critically, the existing Somali territory literature reveals a clear and consistent methodological gap: Mohamed (2020) and Hussein & Abdillahi (2025) apply ARIMA to CPI level data across different Somali territories, while Ali & Mohamed (2022) employ ANN and STL methods for Puntland's CPI and across all three studies, no SARIMA framework is applied to a CPI-derived monthly inflation rate series. This gap precludes identification of the rate of price change and the seasonal fluctuations that are central to understanding Somalia's inflation dynamics, particularly given the pronounced intra year seasonality documented in the SNBS data. The present study directly addresses this gap by applying a SARIMA framework to a monthly CPI-derived inflation rate series spanning February 2018 to December 2024, offering a methodologically rigorous, institutionally grounded, and policy-relevant contribution to the empirical literature on inflation forecasting in fragile and conflict-affected economies.

3. Methodology

This study employs the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, originally developed by Box and Jenkins (1976) and subsequently formalised by Box et al. (2015), to model and forecast Somalia's monthly inflation dynamics. The SARIMA framework is adopted as a direct extension

of the Autoregressive Integrated Moving Average (ARIMA) class of models, which constitutes one of the most widely applied and theoretically grounded approaches to univariate time-series forecasting in the econometrics literature. ARIMA models exploit the temporal autocorrelation structure embedded in a stationary time series by expressing the current value of a variable as a linear function of its own past values, past forecast errors, and, where required, differenced transformations of the series to induce stationarity. The model is composed of three interacting components: The Autoregressive (AR) component, which models the dependence of the current observation on a finite number of its own lagged values; the Moving Average (MA) component, which accounts for the influence of past stochastic shocks or forecast errors on the current value; and the Integrated (I) component, which captures the degree of non-seasonal differencing necessary to render a non-stationary series stationary prior to estimation.

3.1. Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is formally denoted as ARIMA(p, d, q), where p , d , and q are non-negative integers representing the autoregressive order, the degree of non-seasonal differencing, and the moving average order, respectively (Hurvich & Tsai, 1989; Wolters & Kirchgässner, 2007; Kleiber & Zeileis, 2008). The autoregressive order p specifies the number of past values of the series used to explain its current value, the differencing order d denotes the number of successive first-difference transformations required to induce stationarity in a non-stationary series, and the moving average order q specifies the number of past forecast errors incorporated into the model. When $d = 0$, indicating that the series is stationary at its observed level and requires no differencing transformation, the ARIMA(p, d, q) specification reduces to a stationary ARMA(p, q) process. The general scalar representation of the ARIMA(p, d, q) model is expressed as:

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (1)$$

or equivalently in compact summation form:

$$Y_t = \mu + \sum_{k=1}^p \phi_k Y_{t-k} + \varepsilon_t + \sum_{k=1}^q \theta_k \varepsilon_{t-k} \quad (2)$$

where Y_t denotes the monthly inflation series after the application of d differencing operations, μ is a constant term representing the unconditional mean of the process, $\{\phi_1, \phi_2, \dots, \phi_p\}$ are the autoregressive coefficients governing the degree of short-run serial persistence, $\{\theta_1, \theta_2, \dots, \theta_q\}$ are the moving average coefficients governing the propagation of past innovations, and ε_t is a white-noise disturbance term satisfying $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma^2 < \infty$, and $E(\varepsilon_t \varepsilon_s) = 0$ for all $t \neq s$.

Using the backshift operator L , where $LY_t = Y_{t-1}$, Equations (1) and (2) can be expressed in the more compact polynomial form:

$$\phi_p(L)(1 - L)^d Y_t = \mu + \theta_q(L)\varepsilon_t \quad (3)$$

where $\phi_p(L)$ and $\theta_q(L)$ are the non-seasonal autoregressive and moving average lag polynomials, defined respectively as:

$$\phi_p(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p \quad (4)$$

$$\theta_q(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q \quad (5)$$

and the differencing polynomial $(1 - L)^d$ applies d successive first differences to the series prior to estimation. Since unit-root testing in the present study confirms that the monthly inflation series is

stationary at level — that is, $d = 0$ — the differencing polynomial reduces to unity, and no transformation of the observed series is required prior to modelling. The ARIMA($p, 0, q$) specification therefore applies directly to the observed monthly inflation series throughout.

3.2. Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

Although the ARIMA framework described in Section 3.1 provides an effective representation of non-seasonal autocorrelation dynamics, it is structurally insufficient for monthly economic time series that exhibit systematic and recurring intra-year fluctuations. Modelling such series with a purely non-seasonal specification would either fail to capture the periodic patterns or require an unrealistically large number of autoregressive and moving average terms, compromising parsimony and estimation efficiency. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model addresses this limitation by augmenting the ARIMA framework with a set of seasonal polynomials that directly parameterise the autocorrelation structure at multiples of the seasonal period s . Following Box et al. (2015), the SARIMA model is expressed as a multiplicative seasonal process and is formally denoted:

$$SARIMA(p, d, q)(P, D, Q)_s$$

where p, d , and q retain their definitions from Section 3.1 as the non-seasonal autoregressive, differencing, and moving average orders, respectively; P, D , and Q denote the seasonal autoregressive order, the degree of seasonal differencing, and the seasonal moving average order, respectively; and s specifies the number of time periods constituting one complete seasonal cycle. For monthly data, $s = 12$, corresponding to an annual periodicity, a choice empirically supported in the present study by the prominent autocorrelation spike observed at lag 12 in the sample ACF. The multiplicative structure of the model allows the seasonal and non-seasonal dynamics to interact parsimoniously, capturing both within-year short-run persistence and cross-year seasonal recurrence without a proliferation of freely estimated parameters.

The full SARIMA(p, d, q)(P, D, Q) $_s$ model is expressed as:

$$\Phi P(L^s) \phi_p(L) (1 - L)^d (1 - L^s)^D Y_t = \mu + \Theta Q(L^s) \theta_\phi(L) \varepsilon_t \quad (6)$$

where the four lag polynomials are defined as:

$$\phi_p(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p \quad (7)$$

$$\Phi P(L^s) = 1 - \Phi_1 L^s - \Phi_2 L^{2s} - \dots - \Phi P L^{Ps} \quad (8)$$

$$\theta_\phi(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_\phi L^\phi \quad (9)$$

$$\Theta Q(L^s) = 1 + \Theta_1 L^s + \Theta_2 L^{2s} + \dots + \Theta Q L^{Os} \quad (10)$$

In Equation (6), Y_t represents the monthly inflation series after the application of d non-seasonal and D seasonal differencing operations. The seasonal differencing operator $(1 - L^s)^D$ removes stochastic seasonality by computing successive seasonal differences of the form $y_t - y_{t-s}$, while the non-seasonal differencing operator $(1 - L)^d$ removes non-seasonal stochastic trends. The scalar parameters $\{\phi_1, \dots, \phi_p\}$ and $\{\Phi_1, \dots, \Phi_P\}$ govern the non-seasonal and seasonal autoregressive dynamics, respectively, capturing the degree to which current inflation is explained by its own recent and seasonally lagged past values. The parameters $\{\theta_1, \dots, \theta_\phi\}$ and $\{\Theta_1, \dots, \Theta_Q\}$ govern the corresponding non-seasonal and seasonal moving average components, capturing the propagation of past innovations through the series at non-seasonal and seasonal lags. The constant μ represents the unconditional mean of the differenced series, and ε_t is the white-noise disturbance term defined in Section 3.1.

In the present study, unit-root testing confirms that the monthly inflation series requires neither non-seasonal nor seasonal differencing, yielding $d = 0$ and $D = 0$. Both differencing polynomials therefore reduce to unity, and Y_t is equivalent to the observed monthly inflation series throughout. The selected specification, SARIMA(1, 0, 0)(1, 0, 0)₁₂, accordingly involves only the non-seasonal AR(1) polynomial $\phi_1(L)$ and the seasonal AR(1) polynomial $\Phi_1(L^{12})$. Substituting into Equation (6) and expanding yields the following estimating equation:

$$y_t = \mu + \phi_1 y_{t-1} + \Phi_1 y_{t-12} - \phi_1 \Phi_1 y_{t-13} + \varepsilon_t \quad (11)$$

Equation (11) makes transparent the precise structure of the fitted model. Current monthly inflation is jointly determined by its value in the immediately preceding month, capturing short-run non-seasonal persistence; its value in the same month of the prior year, capturing the dominant annual seasonal recurrence; and a multiplicative interaction term at lag 13, which arises naturally from the multiplicative SARIMA structure and reflects how short-run persistence propagates across the seasonal cycle. The white-noise disturbance ε_t absorbs all remaining unexplained variation.

3.3. Box-Jenkins Estimation Procedure

The study follows the iterative Box–Jenkins procedure (Box et al., 2015), comprising three sequential stages: model identification, in which stationarity is confirmed and candidate lag structures are selected via the ACF and PACF; parameter estimation, in which model coefficients are estimated by Maximum Likelihood Estimation (MLE) and competing specifications are ranked by AIC and BIC; and diagnostic checking, in which residuals are tested for white noise using the Portmanteau Q-statistic — with failure returning the procedure to re-identification. The general steps are illustrated in Figure 1.

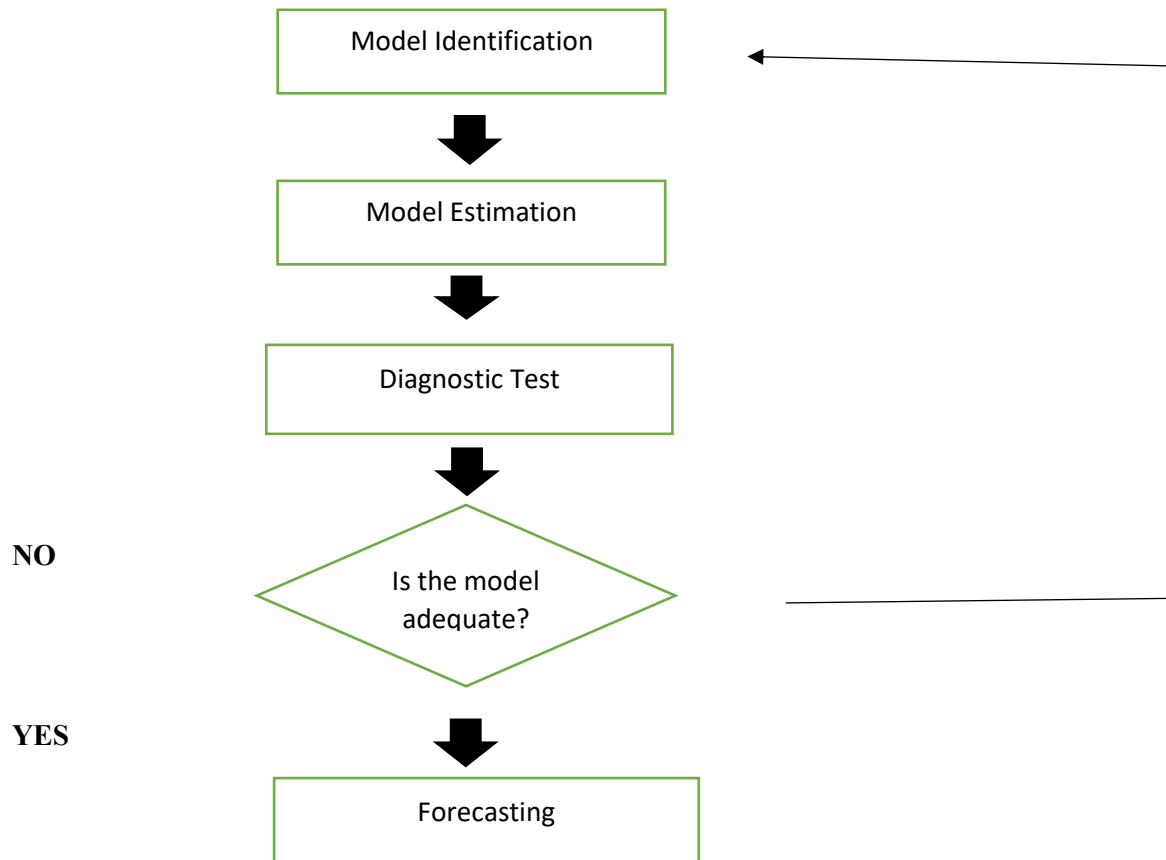


Figure 1. Stages of Box-Jenkins Method

3.4. Data

This study utilises secondary monthly Consumer Price Index (CPI) data sourced from the Somalia National Bureau of Statistics (SNBS), covering the period January 2018 to December 2024 — the full extent of available monthly observations at the time of analysis. To align the data with the study's forecasting objective, the CPI level series was transformed into a monthly inflation rate series by computing the month-on-month percentage change in the CPI at each time period t . This transformation yields a stationary measure of short-run price dynamics that is more analytically appropriate for seasonal time-series modelling than the non-stationary CPI level. The monthly inflation rate is defined as:

$$\pi_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100$$

where π_t denotes the monthly inflation rate at time t , expressed as a percentage; CPI_t and CPI_{t-1} denote the Consumer Price Index in the current month t and the immediately preceding month $t-1$, respectively. A positive value of π_t indicates a month-on-month increase in the general price level, while a negative value indicates a month-on-month decline. The resulting series π_t constitutes the dependent variable throughout all subsequent stages of the empirical analysis.

4. Results

4.1. Model Identification

4.1.1. Data Inspection

Prior to formal modelling, the monthly inflation series was subjected to visual inspection to assess its broad statistical properties and identify any apparent patterns warranting further investigation. Figure 2 plots the month-on-month inflation rate for Somalia over the period February 2018 to December 2024, comprising 83 observations with a standard deviation of approximately 1.04 percentage points. The series exhibits no discernible deterministic trend, fluctuating around a relatively stable mean throughout the sample period — a preliminary indication of level stationarity that is consistent with the behaviour expected of a properly transformed inflation rate series. Both positive and negative realisations are observed across the sample, with several pronounced spikes indicating episodic surges in monthly price pressures, interspersed with periods of mild deflation. Of particular note is the systematic recurrence of these fluctuations at regular intra-year intervals, suggesting the presence of seasonal periodicity in the data-generating process. This visual evidence of potential seasonality motivates the formal stationarity and autocorrelation analysis conducted in Sections 4.1.2 and 4.1.3.

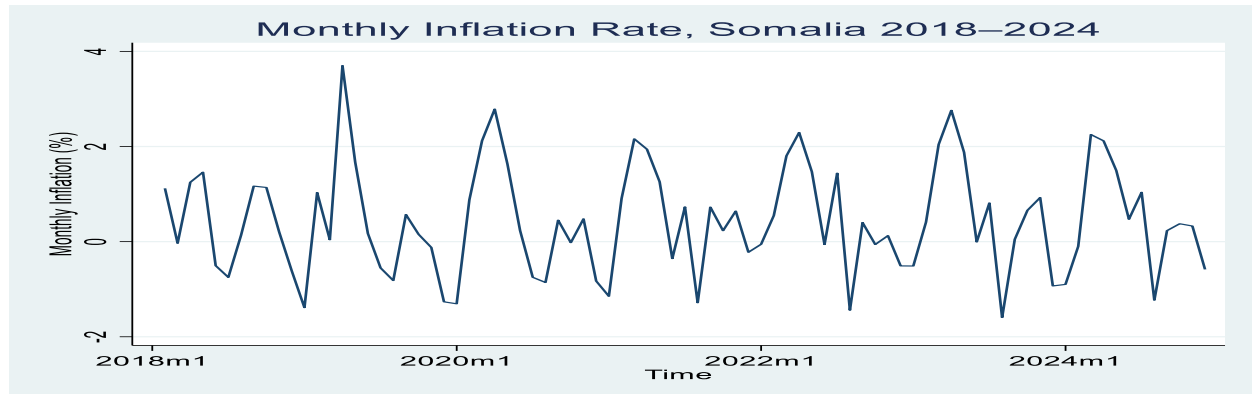


Figure 2. Monthly Inflation Rate between January 2018 to December 2024.

4.1.2. Stationarity Analysis

Formal confirmation of stationarity is a necessary precondition for ARIMA-class modelling, as the theoretical properties of the autoregressive and moving average representations are defined only for covariance-stationary processes. To this end, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests were applied to the monthly inflation series under two alternative specifications — intercept only, and intercept with linear trend — to ensure that the stationarity conclusion is robust to the assumed deterministic structure of the process. The ADF test augments the standard Dickey-Fuller regression with lagged difference terms to correct for serial correlation in the residuals, while the PP test employs a non-parametric correction to the test statistic to account for heteroscedasticity and autocorrelation, thereby providing a complementary and more robust assessment under general error processes (Phillips & Perron, 1988).

The results, reported in Table 1, are unambiguous. Under both the intercept-only and intercept-with-trend specifications, the ADF and PP test statistics are large in absolute value and statistically significant at the 1% level, decisively rejecting the null hypothesis of a unit root. The monthly inflation series is therefore confirmed to be integrated of order zero — $I(0)$ — indicating that it is stationary at its observed level and requires no differencing transformation prior to modelling. Accordingly, both the non-seasonal and seasonal differencing orders are set to zero throughout the analysis ($d = 0$, $D = 0$), and the SARIMA specification is applied directly to the observed inflation series.

Table 1. Unit Root Tests for Stationarity

Test	Specification	Test Statistic	5% Critical Value	P-value
ADF	Intercept	-6.159***	-2.904	0.0000
	Intercept and trend	-6.121***	-3.468	0.0000
PP	Intercept	-6.036***	-2.904	0.0000

Intercept and trend	-5.995***	-3.468	0.0000
---------------------	-----------	--------	--------

Note: Critical values are reported at the 5% significance level.

4.1.3. Autocorrelation and Partial Autocorrelation Analysis

Having confirmed the stationarity of the monthly inflation series, the sample Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were examined to characterise the autocorrelation structure of the series and guide the selection of candidate model specifications. The ACF measures the total linear correlation between the series and its lagged values at each displacement, while the PACF isolates the direct correlation at each lag after removing the confounding influence of all intervening lags — together, their patterns provide the primary empirical basis for identifying the autoregressive and moving average orders in the Box–Jenkins framework.

Inspection of the ACF plot (Figure 3) reveals statistically significant spikes at seasonal lags 12 and 24, indicating strong and persistent annual seasonal dependence in the monthly inflation series. This pattern is characteristic of a seasonal autoregressive process, in which the current month's inflation is systematically related to its value in the same month of preceding years. The PACF plot (Figure 4) displays a dominant spike at seasonal lag 12 with no significant spike at lag 24, consistent with a seasonal AR(1) process, and a moderate spike at non-seasonal lag 1, suggesting the additional presence of short-run non-seasonal autoregressive persistence. Together, these patterns provide clear empirical support for the inclusion of both a non-seasonal AR(1) term and a seasonal AR(1) term in the candidate model set.

Based on this evidence, nine candidate specifications were estimated for comparative evaluation: ARIMA(1,0,0), ARIMA(0,0,1), ARIMA(1,0,1), ARIMA(2,0,0), SARIMA(0,0,0)(1,0,0)₁₂, SARIMA(1,0,0)(1,0,0)₁₂, SARIMA(0,0,1)(1,0,0)₁₂, SARIMA(1,0,1)(1,0,0)₁₂, and SARIMA(2,0,0)(1,0,0)₁₂. Each specification was assessed on the basis of AIC, BIC, coefficient significance, and residual white-noise diagnostics, as reported in Section 4.2.

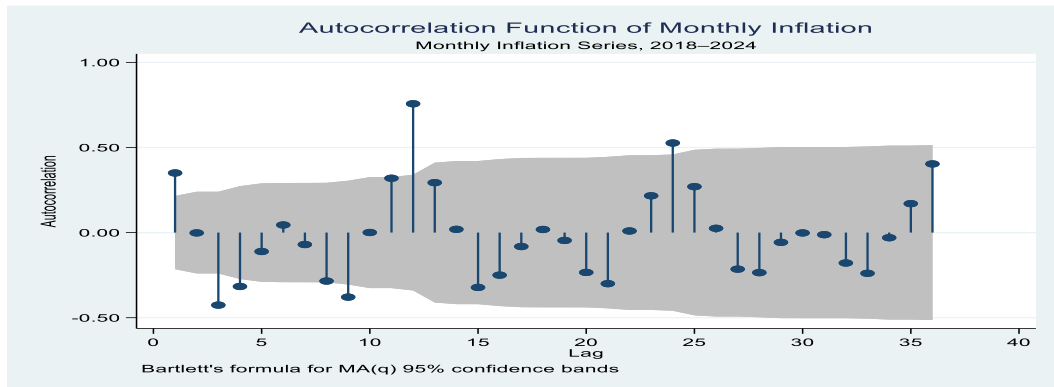


Figure 3. Autocorrelation Function (ACF)

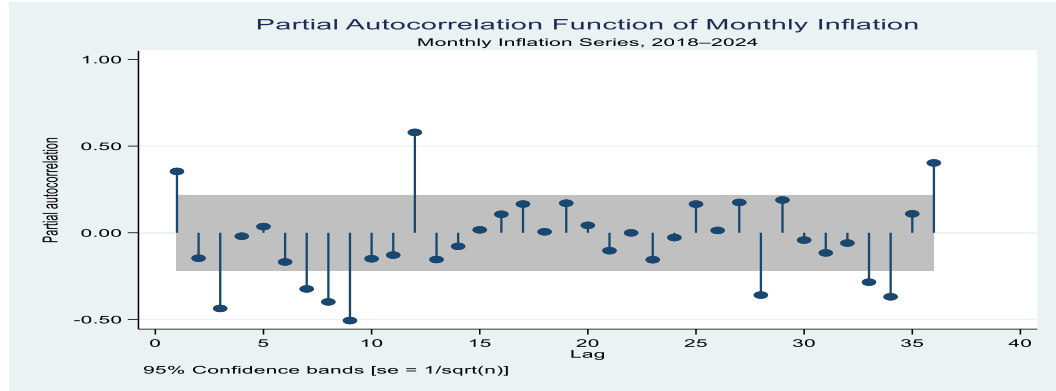


Figure 4. Partial Autocorrelation Function (PACF)

4.2. Estimation

4.2.1. Model Selection

Following the identification of candidate lag structures from the ACF and PACF analysis in Section 4.1.3, nine ARIMA and SARIMA specifications were estimated and evaluated to determine the most parsimonious and statistically adequate model for forecasting Somalia's monthly inflation. Model selection was conducted in two steps: first, competing specifications were ranked by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), both of which reward goodness of fit while penalising model complexity — with lower values indicating a superior balance between fit and parsimony; second, the top-ranked specifications were subjected to residual diagnostic testing to verify white-noise adequacy, consistent with the Box–Jenkins requirement that a well-specified model leaves no exploitable autocorrelation structure in the residuals.

The estimation results are reported in Table 2. Non-seasonal ARIMA specifications — ARIMA(1,0,0), ARIMA(0,0,1), ARIMA(1,0,1), and ARIMA(2,0,0) — produced substantially higher AIC and BIC values than all SARIMA alternatives, with AIC values ranging from 249.16 to 250.65, confirming that the non-seasonal component alone is insufficient to capture the periodic structure of the inflation series. Specifications incorporating a seasonal MA(1) component were also estimated but similarly produced higher information criteria values than their seasonal AR(1) counterparts and were accordingly excluded. Among the seasonal AR(1,0,0)₁₂ specifications, SARIMA(0,0,0)(1,0,0)₁₂ achieved the lowest BIC of 173.91; however, this specification failed the Portmanteau white-noise test at lag 12 ($Q = 21.81$, $p = 0.0397$), indicating that significant residual autocorrelation remains and the model is therefore inadequate for forecasting purposes. The SARIMA(1,0,0)(1,0,0)₁₂ specification produced AIC = 167.53 and BIC = 177.21 and, critically, passed the Portmanteau diagnostic at both lag 12 ($p = 0.1275$) and lag 24 ($p = 0.3578$), confirming that its residuals are consistent with a white-noise process. On the combined basis of competitive information criteria and full diagnostic adequacy, SARIMA(1,0,0)(1,0,0)₁₂ is selected as the final model for estimation and forecasting.

Table 2. Model Selection Criteria for Candidate ARIMA and SARIMA Specifications

Model	Log-Likelihood	AIC	BIC	df
ARIMA(1,0,0)	−121.5794	249.1589	256.4154	3
ARIMA(0,0,1)	−122.0656	250.1311	257.3876	3

Model	Log-Likelihood	AIC	BIC	df
ARIMA(1,0,1)	-121.3239	250.6478	260.3231	4
ARIMA(2,0,0)	-120.6995	249.3990	259.0744	4
SARIMA(0,0,0)(1,0,0) ₁₂	-80.3255	166.6510	173.9075	3
SARIMA(1,0,0)(1,0,0)₁₂	-79.7661	167.5322	177.2076	4
SARIMA(0,0,1)(1,0,0) ₁₂	-79.8241	167.6482	177.3236	4
SARIMA(1,0,1)(1,0,0) ₁₂	-80.3108	170.6216	182.7158	5
SARIMA(2,0,0)(1,0,0) ₁₂	-79.7332	169.4663	181.5605	5

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; df = number of estimated parameters. Lower AIC and BIC values indicate a superior balance between model fit and parsimony. The selected model is highlighted in bold. Selection was based on the combined criterion of competitive information criteria and passing the Portmanteau white-noise residual diagnostic at both lag 12 and lag 24.

4.2.2. Parameter Estimation Results

Table 3 reports the estimated parameters of the selected SARIMA(1,0,0)(1,0,0)₁₂ model, estimated by conditional Maximum Likelihood Estimation over 83 monthly observations spanning February 2018 to December 2024. The model produced a log-likelihood of -79.7661, and the Wald chi-square statistic of 164.61 ($p < 0.001$) confirms the joint statistical significance of the parameter vector, indicating that the model as a whole provides a meaningful characterisation of the inflation data-generating process.

The constant term is positive but statistically insignificant ($\mu = 0.3941$, $p = 0.236$), indicating the absence of a strong deterministic mean component in monthly inflation once seasonal dynamics are controlled for. The non-seasonal AR(1) coefficient is similarly positive but insignificant ($\phi_1 = 0.1177$, $p = 0.428$), reflecting weak short-run month-to-month persistence in inflation after accounting for the dominant seasonal structure. Notwithstanding its individual insignificance, the AR(1) term was retained on diagnostic grounds: its exclusion — assessed through the parsimonious SARIMA(0,0,0)(1,0,0)₁₂ alternative — produced a Portmanteau Q-statistic of 21.81 ($p = 0.0397$) at lag 12, indicating residual serial correlation at the 5% significance level and a violation of the white-noise requirement. Retaining the AR(1) term eliminates this autocorrelation ($Q = 17.63$, $p = 0.1275$), and its inclusion is therefore necessary for model adequacy consistent with the Box–Jenkins diagnostic criterion.

The dominant finding is the seasonal AR(12) coefficient, which is positive, large in magnitude, and highly significant at the 1% level ($\Phi_1 = 0.8274$, $p < 0.001$). This estimate implies that monthly inflation in any given month is strongly and persistently determined by inflation in the corresponding month of the prior year, confirming that annual seasonal recurrence is the primary driver of Somalia's monthly inflation dynamics. The magnitude of this coefficient — approaching but remaining strictly below the unit-root boundary — reflects near-persistent seasonal behaviour, a finding further corroborated by the rolling-window stability analysis in Section 4.6. The sigma parameter ($\sigma = 0.5819$, $p < 0.001$) is highly significant, quantifying the standard deviation of the white-noise innovation process and confirming that residual variation, while present, is well-characterised by the assumed homoscedastic disturbance structure.

Table 3. Estimated Parameters of the SARIMA(1,0,0)(1,0,0)₁₂ Model

Parameter	Coefficient	Std. Error	z-statistic	p-value
Constant	0.3941	0.3325	1.19	0.236
AR(1)	0.1177	0.1484	0.79	0.428
Seasonal AR(12)	0.8274***	0.0685	12.08	0.000
Sigma	0.5819***	0.0294	19.83	0.000
Number of observations: 83 Log Likelihood: -79.7661 Wald χ^2 : 164.61 Prob > χ^2 : 0.000				

Note: *** denotes significance at the 1% level.

4.3. Residual Diagnostic Analysis

Following estimation, the adequacy of the selected SARIMA(1,0,0)(1,0,0)₁₂ model was assessed through residual diagnostic testing to verify that the estimated residuals are consistent with a white-noise process — a necessary condition for correct model specification and forecast validity. The Portmanteau Q-statistic was applied at lag 12 and lag 24, testing the joint null hypothesis that all residual autocorrelations up to the specified lag are equal to zero.

The results, reported in Table 4, provide no evidence of misspecification. The null hypothesis of white-noise residuals is not rejected at either lag 12 ($Q = 17.63$, $p = 0.1275$) or lag 24 ($Q = 25.91$, $p = 0.3578$), confirming that the model has fully absorbed the autocorrelation structure of the monthly inflation series. The residual plot in Figure 5 corroborates this conclusion, with residuals fluctuating randomly around zero without persistent pattern or trend. Figure 6 further confirms that all inverse roots of the AR polynomial lie strictly within the unit circle, satisfying the dynamic stability condition required for valid forecasting.

Table 4. Portmanteau White-Noise Test of Residuals

Diagnostic Test	Lag	Q-statistic	p-value
Portmanteau white-noise test	12	17.6263	0.1275
Portmanteau white-noise test	24	25.9081	0.3578

Note: Null hypothesis: residuals are white noise. Rejection at $p < 0.05$.

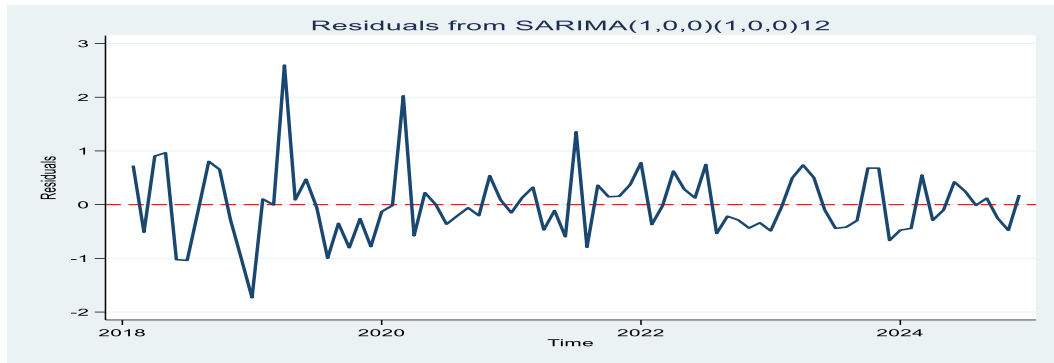


Figure 5. Residuals from SARIMA $(1,0,0)(1,0,0)_{12}$

The dynamic stability of the SARIMA $(1,0,0)(1,0,0)_{12}$ model was formally assessed by examining the inverse roots of the autoregressive characteristic polynomial. A necessary and sufficient condition for the covariance stationarity of an autoregressive process is that all roots of the characteristic polynomial lie strictly outside the complex unit circle — equivalently, that all inverse roots lie strictly within it. Figure 6 confirms that this condition is satisfied: all inverse roots are located strictly inside the unit circle, with no root at or near the boundary, thereby ruling out unit-root or near-integrated behaviour in the fitted process. The estimated model is therefore confirmed to be dynamically stable, invertible, and fully appropriate for the generation of valid out-of-sample inflation forecasts.

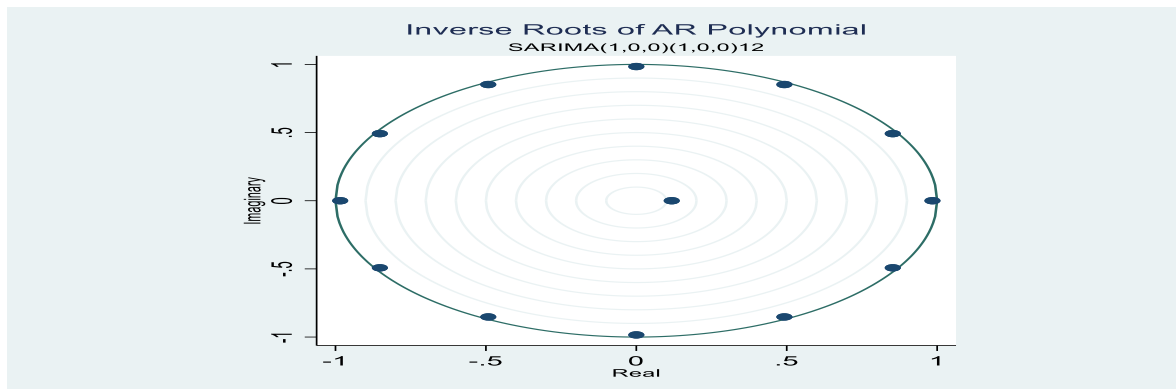


Figure 6. Inverse Roots of AR Polynomial — SARIMA $(1,0,0)(1,0,0)_{12}$

4.4. Inflation Forecasts

Following successful model identification, estimation, and diagnostic validation, the SARIMA $(1,0,0)(1,0,0)_{12}$ specification was employed to generate monthly out-of-sample inflation forecasts for the period January 2025 to December 2026, together with 95% confidence intervals to quantify the uncertainty surrounding the projected inflation path.

The point forecasts and associated confidence intervals are reported in Table 5 and illustrated in Figure 7. The forecasts indicate that Somalia's monthly inflation is expected to remain moderate in level but exhibit pronounced seasonal variability over the forecast horizon, driven primarily by the dominant seasonal

AR(12) structure identified in the estimation stage. In 2025, the highest monthly inflation is projected in March, April, and May, with point forecasts of 1.9310%, 1.8215%, and 1.3056%, respectively, reflecting the recurring seasonal upward pressure on food prices during the first half of the year. Temporary deflationary episodes are projected in January (−0.6614%), August (−0.9492%), and December (−0.4150%). An analogous seasonal pattern is projected for 2026, with peak inflation again concentrated in March (1.6657%), April (1.5751%), and May (1.1483%), at moderately attenuated magnitudes relative to 2025.

The 95% confidence intervals widen progressively across the forecast horizon, consistent with the standard property that forecast uncertainty accumulates over longer horizons. The lower confidence bounds remain strictly positive only in March, April, and May of 2025, the months for which positive inflation can be asserted with 95% statistical confidence. For all remaining months, the confidence intervals straddle zero, indicating that deflationary outcomes cannot be statistically excluded. These findings highlight the importance of communicating forecast uncertainty alongside point estimates when informing fiscal planning, wage adjustment, and social protection policy decisions.

Table 5. Forecasted Monthly Inflation with 95% Confidence Intervals (2025–2026)

2025				2026			
Period	Forecast (%)	Lower 95% FI	Upper 95% FI	Period	Forecast (%)	Lower 95% FI	Upper 95% FI
January	-0.6614	-1.8020	0.4791	January	-0.4793	-1.9658	1.0073
February	-0.0118	-1.1602	1.1367	February	0.0583	-1.4324	1.5490
March	1.9310	0.7824	3.0795	March	1.6657	0.1750	3.1565
April	1.8215	0.6729	2.9700	April	1.5751	0.0844	3.0659
May	1.3056	0.1571	2.4542	May	1.1483	-0.3424	2.6391
June	0.4580	-0.6906	1.6066	June	0.4470	-1.0438	1.9377
July	0.9263	-0.2222	2.0749	July	0.8345	-0.6563	2.3252
August	-0.9492	-2.0978	0.1993	August	-0.7174	-2.2082	0.7734
September	0.2597	-0.8888	1.4083	September	0.2829	-1.2078	1.7737
October	0.3795	-0.7690	1.5281	October	0.3821	-1.1087	1.8728
November	0.3403	-0.8083	1.4888	November	0.3495	-1.1412	1.8403
December	-0.4150	-1.5636	0.7336	December	-0.2754	-1.7661	1.2154

Figure 7 presents the full inflation series alongside the out-of-sample forecasts and 95% confidence bands, with the vertical dotted line demarcating the boundary between the in-sample and forecast periods at January 2025. During the in-sample period, the fitted values closely track the historical trajectory of monthly inflation, confirming that the model successfully reproduces the dominant seasonal fluctuations of the data-generating process. During the forecast period, the projected series exhibits a clearly recurring seasonal pattern driven by the estimated seasonal AR(12) coefficient of 0.8274, which propagates the annual seasonal structure of past inflation forward across the forecast horizon, reinforcing the conclusion that seasonal persistence is the primary determinant of Somalia's monthly inflation dynamics.

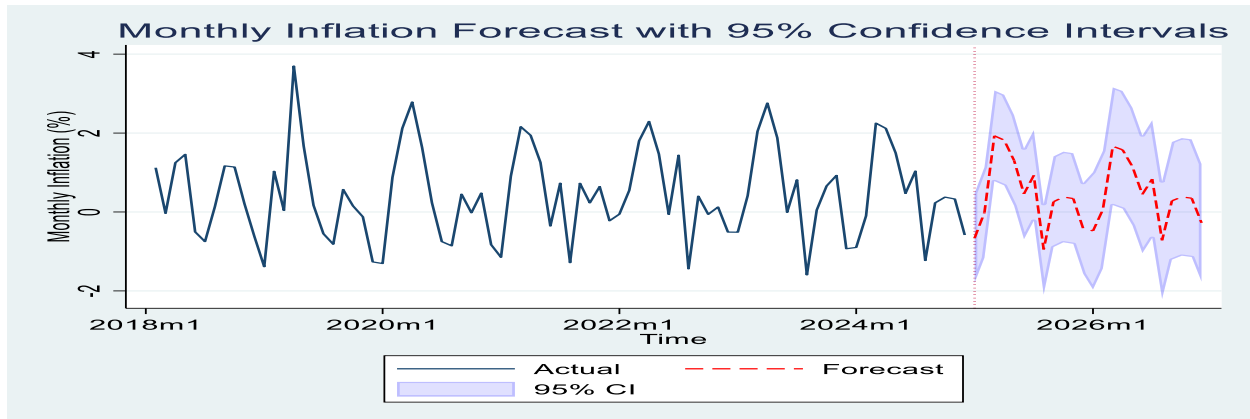


Figure 7. Actual and Forecasted Monthly Inflation with 95% Confidence Intervals

4.5. Out-of-Sample Forecast Accuracy

The predictive performance of the $SARIMA(1,0,0)(1,0,0)_{12}$ model was evaluated through a hold-out validation exercise, in which the model was re-estimated over the training period February 2018 to December 2023 and one-step-ahead point forecasts were generated for the twelve months of 2024 and compared against the corresponding realised inflation rates.

The accuracy metrics are reported in Table 6. The Mean Absolute Error (MAE) of 0.2909 percentage points and Root Mean Squared Error (RMSE) of 0.3399 percentage points are both substantially below the series standard deviation of 1.04 percentage points — equivalent to approximately 28% and 33% of the unconditional variability of the series, respectively — indicating that the model generates forecasts of high practical accuracy. The Mean Absolute Percentage Error (MAPE) was not computed, as the presence of near-zero and negative realisations in the monthly inflation series renders percentage-based error metrics numerically unreliable and theoretically inappropriate for this class of data. Collectively, the out-of-sample results confirm that the $SARIMA(1,0,0)(1,0,0)_{12}$ model produces statistically reliable and practically accurate forecasts of Somalia's monthly inflation, supporting its suitability for policy-relevant short-term forecasting applications.

Table 6. Out-of-Sample Forecast Accuracy Evaluation (2024)

Metric	Value
Mean Absolute Error (MAE)	0.2909
Root Mean Squared Error (RMSE)	0.3399

Taken together, the out-of-sample evaluation confirms that the $SARIMA(1,0,0)(1,0,0)_{12}$ model not only provides a well-fitting characterisation of the historical inflation dynamics but also delivers reliable and accurate out-of-sample forecasts, with MAE and RMSE values well within acceptable bounds for policy-relevant short-term inflation forecasting in a data-constrained environment such as Somalia.

4.6. Robustness Check

To assess the temporal stability of the dominant seasonal parameter, a rolling-window estimation of the seasonal AR(12) coefficient was conducted over the period January 2023 to January 2025. As illustrated in Figure 8, the coefficient remains stable throughout the evaluation window, ranging between 0.78 and 0.91 with no evidence of structural breaks, systematic drift, or directional trend. Although the upper end of this range approaches the seasonal unit-root boundary, all estimates remain strictly below unity and the inverse root test confirms dynamic stability throughout. The 95% confidence bands remain consistently positive and relatively narrow across all estimation windows, confirming the precision of the estimate. These results establish that the annual seasonal persistence characterising Somalia's monthly inflation has remained structurally stable over the post-sample period, providing additional empirical support for the reliability and robustness of the SARIMA(1,0,0)(1,0,0)₁₂ model's forward projections.

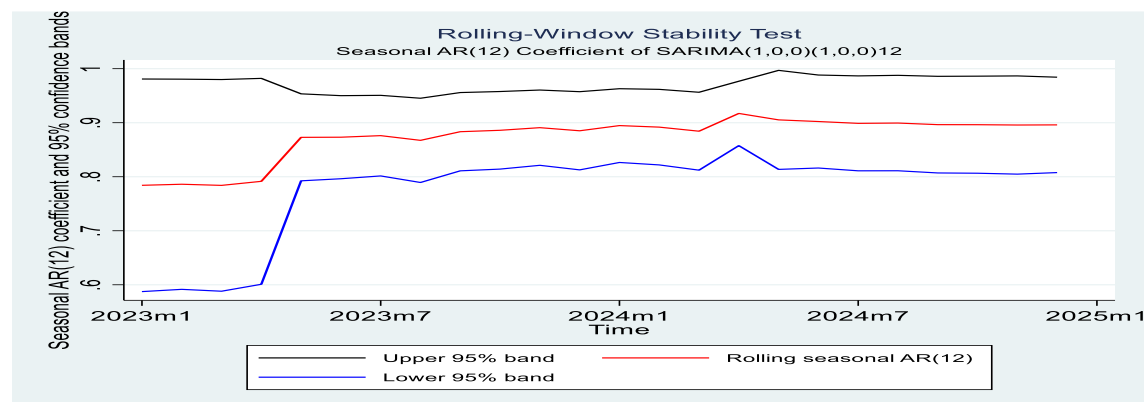


Figure 8. Rolling-Window Stability Test

5. Conclusion

This study applied a Seasonal Autoregressive Integrated Moving Average (SARIMA) framework to model and forecast Somalia's monthly CPI-derived inflation rate over the period February 2018 to December 2024. By modelling the month-on-month inflation rate rather than the CPI level, the study addresses an important methodological gap in the Somali-territory inflation-forecasting literature and provides a more direct assessment of short-run price dynamics.

Following the Box–Jenkins procedure, the analysis involved stationarity testing, autocorrelation analysis, model identification, parameter estimation, residual diagnostics, forecast evaluation, and robustness assessment. The Augmented Dickey–Fuller and Phillips–Perron tests confirmed that the monthly inflation series is stationary at level, $I(0)$, requiring neither non-seasonal nor seasonal differencing. Inspection of the ACF and PACF indicated a dominant annual seasonal structure at lag 12, together with moderate short-run persistence. Among nine candidate specifications, SARIMA(1,0,0)(1,0,0)₁₂ was selected as the optimal model based on information criteria and Portmanteau residual diagnostics.

The empirical findings show that Somalia's monthly inflation is strongly characterized by annual seasonal recurrence. The estimated seasonal AR(12) coefficient of 0.8274 is positive, large in magnitude, and statistically significant at the 1% level, indicating that inflation in a given month is strongly related to inflation in the corresponding month of the previous year. The out-of-sample hold-out evaluation for 2024 produced a Mean Absolute Error of 0.2909 percentage points and a Root Mean Squared Error of 0.3399 percentage points, confirming strong short-term predictive performance. Rolling-window estimation further showed that the seasonal parameter remained stable, ranging between 0.78 and 0.91, with no evidence of systematic drift or structural instability.

The two-year forecasts for 2025 and 2026 suggest that Somalia's monthly inflation is likely to remain moderate in average level but marked by recurring seasonal variation. The model projects relatively higher inflation in March, April, and May, while temporary deflationary episodes are projected in January, August, and December. These projected seasonal peaks are consistent with possible food-supply and demand-side pressures, including post-deyr market conditions and Ramadan/Eid-related consumption patterns; however, they should be interpreted as statistical seasonal regularities rather than direct causal effects, since the univariate SARIMA model does not identify the structural drivers of inflation.

5.1. Policy Implications

The findings carry several important implications for macroeconomic surveillance and policy planning in Somalia. First, the statistically predictable March–May inflation peak should be incorporated into annual fiscal planning, procurement scheduling, and social protection programming. Advance preparation for this seasonal window may help reduce the welfare impact of price increases on low-income and food-insecure households.

Second, the projected deflationary episodes in January, August, and December should not be interpreted automatically as signs of economic improvement. Instead, policymakers should monitor whether these periods reflect normal seasonal price adjustment or weaker household demand, deteriorating purchasing power, or localized supply disruptions.

Third, the forecasting performance of the SARIMA model provides a useful empirical basis for institutionalizing monthly inflation monitoring within the Somalia National Bureau of Statistics. A regular seasonal forecasting system would strengthen macroeconomic surveillance, improve budget planning, and support timely communication of inflation risks to government agencies, development partners, and humanitarian actors.

Fourth, SARIMA-based forecasts should be used as a baseline forecasting tool rather than as a stand-alone policy instrument. Recent post-sample evidence from Mohamed (2026) shows that Somalia remains highly exposed to external fuel-price shocks, import-cost pressures, drought, and regional market disruptions. Therefore, seasonal forecasting should be complemented by real-time commodity-price monitoring, especially for fuel, wheat, rice, cooking oil, sugar, transport costs, and electricity-related prices.

5.2. Limitations and Directions for Future Research

Several limitations should be acknowledged. First, the estimation sample consists of 83 monthly observations, which limits the statistical power of the model selection process and restricts the use of more data-intensive forecasting methods. As longer CPI series become available, future research should re-estimate the model using extended data and evaluate whether higher-order seasonal specifications improve forecasting performance.

Second, the SARIMA framework is univariate. Although it is well suited for identifying recurring seasonal inflation patterns, it does not incorporate the structural determinants of inflation, such as exchange-rate movements, global fuel prices, import costs, money supply, climatic shocks, or food-market disruptions. Future studies should extend the analysis using ARIMAX, VAR, or other multivariate time-series models to examine how these factors transmit into domestic inflation.

Third, Mohamed (2026) is used in this study only as post-sample contextual evidence and is not included in the estimation of the SARIMA model. The model is estimated using monthly CPI-derived inflation data from February 2018 to December 2024. Sudden shocks such as geopolitical oil-price disruptions, shipping-

cost increases, or drought-related supply failures lie outside the information set of a purely historical univariate model. Future work should therefore explore regime-switching, threshold, or nowcasting models that combine high-frequency market surveillance data with seasonal forecasting.

Fourth, while the SARIMA model demonstrated strong out-of-sample performance for the 2024 hold-out period, future studies should compare its accuracy against ARIMA–GARCH, machine-learning, STL decomposition, and ensemble forecasting methods once longer and more stable datasets become available

Author contributions

Conceptualization, A.M.M.; methodology, A.M.M.; software, A.M.M.; validation, A.M.M.; formal analysis, A.M.M.; investigation, A.M.M.; resources, A.M.M.; data curation, A.M.M.; writing—original draft preparation, A.M.M.; writing—review and editing, A.M.M.; visualization, A.M.M.; project administration, A.M.M. The author has read and agreed to the published version of the manuscript.

Data availability

The data availability statement has been corrected in both the manuscript and the submission system to ensure consistency. The manuscript now states that the data used in the study are publicly available from the Somali National Bureau of Statistics (SNBS), with the processed dataset available from the corresponding author upon reasonable request.

Disclosure statement

The author reports there are no competing interests to declare.

Ethics, consent to participate, and consent to publish declarations: not applicable

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sector

Reference

Ali, A. O., & Mohamed, J. (2022). The optimal forecast model for consumer price index of Puntland state, Somalia. *Quality & Quantity*, 56(6), 4549–4572. <https://doi.org/10.1007/s11135-022-01328-6>

- Boniface, A., & Martin, A. (2019). Time series modeling and forecasting of consumer price index in Ghana. *Journal of Advances in Mathematics and Computer Science*, 1-11. <https://doi.org/10.9734/jamcs/2019/v32i130134>
- Box, G. E., & Jenkins, G. M. (1976). *Times series analysis: Forecasting and control*.
- Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control*. John Wiley & Sons.
- Chavez Hurtado, J. L., & Cortes-Fregoso, J. H. (2013). Forecasting Mexican inflation using neural networks. *CONIELECOMP 2013, 23rd International Conference on Electronics, Communications and Computing*, 32-35. <https://doi.org/10.1109/conielecomp.2013.6525753>
- HURVICH, C. M., & TSAI, C. (1989). Regression and time series model selection in small samples. *Biometrika*, 76(2), 297-307. <https://doi.org/10.1093/biomet/76.2.297>
- Hussein, A., & Abdillahi, A. (2025). Modelling and forecasting Somalia's consumer price index using the ARIMA model. *American Journal of Theoretical and Applied Statistics*, 14(2), 89-98. <https://doi.org/10.11648/j.ajtas.20251402.14>
- Imron, M., Utami, W. D., Khaulasari, H., & Armunanto, F. (2022). Arima model of outlier detection for forecasting consumer price index (Cpi). *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, 16(4), 1259-1270. <https://doi.org/10.30598/barekengvol16iss4pp1259-1270>
- Işığışok, E., Öz, R., & Tarkun, S. (2022). Forecasting and technical comparison of inflation in Turkey with Box-Jenkins (ARIMA) models and the artificial neural network. *Research Anthology on Artificial Neural Network Applications*, 1194-1216. <https://doi.org/10.4018/978-1-6684-2408-7.ch057>
- Kamagaté, A., N'Dri, A. Y., Kouakou, A. K., & Hili, O. (2025). Forecasting the consumer price index using a SARIMA model with GARCH innovations: The case of Cote D'IVOIRE. *Far East Journal of Theoretical Statistics*, 69(3), 383-400. <https://doi.org/10.17654/0972086325018>

- Kirchgässner, G., & Wolters, J. (2007). Introduction to modern time series analysis. <https://doi.org/10.1007/978-3-540-73291-4>
- Kleiber, C., & Zeileis, A. (2008). *Applied econometrics with R*. Springer Science & Business Media.
- Kurniasari, D., Mukhlisin, Z., Wamiliana, W., & Warsono, W. (2023). Performance of the accuracy of forecasting the consumer price index using the garch and Ann methods. *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, 17(2), 0931-0944. <https://doi.org/10.30598/barekengvol17iss2pp0931-0944>
- Kustiara, S., Nur, I. M., & Utami, T. W. (2020). Arch garch method of forecasting consumer price index (Cpi) in Semarang. *Jurnal Litbang Edusaintech*, 1(1), 14-22. <https://doi.org/10.51402/jle.v1i1.3>
- Maiga, Y. M. (2024). Empirical approach to modelling and forecasting inflation using ARIMA model: Evidence from Tanzania. *Journal of Agricultural Studies*, 12(2), 58. <https://doi.org/10.5296/jas.v12i2.21695>
- McAdam, P., & McNelis, P. (2005). Forecasting inflation with thick models and neural networks. *Economic Modelling*, 22(5), 848-867. <https://doi.org/10.1016/j.econmod.2005.06.002>
- Mehdiyev, N., & Enke, D. (2014). Interest rate prediction: A neuro-hybrid approach with data preprocessing. *International Journal of General Systems*, 43(5), 535-550. <https://doi.org/10.1080/03081079.2014.883386>
- Mohamed, A. A. (2026). *Somalia's inflation outlook: Intersections of global oil shocks, import dependence, and climate crises* (Policy Brief No. 003). Somalia National Bureau of Statistics (SNBS). Mogadishu, Somalia.
- Mohamed, J. (2020). Time series modeling and forecasting of Somaliland consumer price index: A comparison of ARIMA and regression with ARIMA errors. *American Journal of Theoretical and Applied Statistics*, 9(4), 143. <https://doi.org/10.11648/j.ajtas.20200904.18>

- Mwanga, Y. (2020). Arima forecasting model for Uganda's consumer price index. *American Journal of Theoretical and Applied Statistics*, 9(5), 238. <https://doi.org/10.11648/j.ajtas.20200905.17>
- Otu, A., George A., O., Jude, O., Hope Ifeyinwa, M., & Andrew I., I. (2014). Application of Sarima models in modelling and forecasting Nigeria's inflation rates. *American Journal of Applied Mathematics and Statistics*, 2(1), 16-28. <https://doi.org/10.12691/ajams-2-1-4>
- PHILLIPS, P. C., & PERRON, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346. <https://doi.org/10.1093/biomet/75.2.335>
- Poudel, O., Kharel, K. R., Acharya, P., Simkhada, D., & Kafle, S. C. (2024). ARIMA modeling and forecasting of national consumer price index in Nepal. *Interdisciplinary Journal of Management and Social Sciences*, 5(1), 105-118. <https://doi.org/10.3126/ijmss.v5i1.62666>
- Purbasari, I. Y., Anggraeny, F. T., & Ardiningrum, N. A. (2020). Time-series modeling for consumer price index forecasting using comparison analysis of autoregressive integrated moving average and artificial neural network. *Proceedings of the International Conference on Culture Heritage, Education, Sustainable Tourism, and Innovation Technologies*, 599-604. <https://doi.org/10.5220/0010369205990604>
- Qasim, T. B., Ali, H., Malik, N., & Liaquat, M. (2021). Forecasting inflation applying ARIMA model with GARCH innovation: The case of Pakistan. *Journal of Accounting and Finance in Emerging Economies*, 7(2), 313-324. <https://doi.org/10.26710/jafee.v7i2.1681>
- Rizwan, M., AsadUllah, M., & Jumani, N. (2025). Forecasting inflation in Pakistan using ARIMA model. *Journal of Finance & Economics Research*. <https://doi.org/10.20547/jfer2510203>
- Somalia National Bureau of Statistics. (2018). *Consumer price index* [Dataset]. Somalia Open Data Portal. Retrieved July 10, 2018, from <http://somalia.opendataforafrica.org/satfjze/consumer-price-index>

Stock, J., & Watson, M. (2006). Why has U.S. inflation become harder to forecast?

<https://doi.org/10.3386/w12324>

Sultana, K. (2013). Forecasting inflation and economic growth of Pakistan by using two time series methods. *International Journal of Business and Economics Research*, 2(6), 174.

<https://doi.org/10.11648/j.ijber.20130206.17>