

FORECASTING GLOBAL OTHER MILD ARABICA COFFEE PRICES USING SARIMA: EVIDENCE FROM MORE THAN 34 YEARS OF MONTHLY DATA

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Abstract

Global Other Mild Arabica coffee prices exhibit substantial volatility associated with climatic, biological, and macroeconomic factors, making baseline forecasting useful for decision-making by traders, farmers, and policymakers. We apply the Box–Jenkins approach to model monthly global Other Mild Arabica coffee prices using data from January 1992 to March 2026 obtained from the Federal Reserve Economic Data (FRED) database. We confirmed non-stationarity of the data using the Augmented Dickey–Fuller test and applied first-order differencing to achieve stationarity. Autocorrelation and partial autocorrelation analyses were performed to guide model identification and forecasting. We selected the SARIMA(2,1,2)(1,0,0)[12] model based on information criteria and residual diagnostic results. The model showed satisfactory in-sample fit, and residuals exhibited no significant autocorrelation. These results were further confirmed by the Ljung–Box test with a p-value greater than 0.05. Forecasts through March 2028 indicate relatively stable point forecasts with moderate month-to-month fluctuations and increasing prediction uncertainty over time. The SARIMA model provides a useful baseline framework for capturing seasonal and non-seasonal variation in coffee prices and for forecasting. The findings offer practical value for risk mitigation and strategic planning in the global coffee market. This study contributes to the existing literature by providing updated forecasts for Other Mild Arabica coffee prices through March 2028 using a robust modeling approach estimated using more than 34 years of monthly data. Future research may benefit from including external variables like climate indicators, exchange rates, and supply chain disruptions to further improve forecasting accuracy.

Keywords: Coffee price forecasting, SARIMA, Box–Jenkins methodology, time series analysis, Arabica coffee, price volatility.

JEL Classification: C22, C53, E37, Q11

1. INTRODUCTION

Coffee is one of the world's most widely traded agricultural commodities and is among the most widely consumed beverages globally. It is cultivated in more than 70 countries, primarily in tropical and subtropical regions. Global coffee production is led by Brazil, Vietnam, Colombia, and Indonesia, with Brazil consistently accounting for the largest share (International Coffee Organization, 2023). The sector is economically important, supporting the livelihoods of millions of farmers, particularly smallholders in developing countries (Food and Agriculture Organization, 2015). Beyond its production scale, coffee plays a central role in global trade and value chains. De Felice et al. (2025) note that coffee is processed into roasted, ground, and soluble forms and distributed worldwide through complex supply networks. Coffee is also a key export commodity for many developing countries, contributing substantially to foreign exchange earnings (Food and Agriculture Organization, 2015). Additionally, the increasing global demand for coffee has expanded market opportunities, particularly in high-income countries (International Coffee Organization, 2023).

Coffee production is highly sensitive to environmental conditions, especially temperature and precipitation, as reported by Chemura et al. (2015). Climate variability can significantly affect coffee yield and quality, making the crop sensitive to climate change (Intergovernmental Panel on Climate Change, 2022). Bunn et al. (2015) state that shifts in climatic suitability may reduce areas appropriate for coffee cultivation in the future, posing risks to long-term supply. Furthermore, pests and diseases such as coffee leaf rust (*Hemileia vastatrix*) have historically caused major disruptions in production, particularly in Latin America (Avelino et al., 2015). These changes in global coffee production due to climatic shocks, pest and disease outbreaks, and exchange rate fluctuations create supply-demand imbalances and cause coffee prices to fluctuate (Pham et al., 2019).

Considering these factors, we examine global Other Mild Arabica coffee price movements using time series analysis, a statistical method that systematically analyzes temporal dynamics of data, identifies underlying patterns such as seasonality, trends, and cyclical fluctuations, and improves forecasting accuracy (Hyndman & Athanasopoulos, 2021; Box et al., 2015). Advances in data analytics and econometric modeling, including advanced statistical models and machine learning, have enhanced the understanding and forecasting of commodity price dynamics (Hyndman & Athanasopoulos, 2021; Makridakis et al., 2018). Among these methods, Seasonal Autoregressive Integrated Moving Average (SARIMA) models are especially appropriate for agricultural commodity prices, which often exhibit both seasonal patterns arising from harvest cycles and short-term price persistence arising from market adjustments (Box et al., 2015). Integrating these analytical techniques with economic principles shows that data-driven methods can enhance understanding of market dynamics and

support more efficient pricing, which is essential for the sustainable development of the global coffee sector (Makridakis et al., 2018).

Despite substantial research on agricultural commodity price forecasting, updated forecasting models for global Other Mild Arabica coffee prices remain useful for supporting decision-making in the current market context. Previous studies have explored coffee price dynamics using various methodologies; however, few studies have employed the Box-Jenkins framework on the most recent data available, particularly amid market shocks observed in recent years. This study addresses this gap by forecasting global coffee prices through March 2028. The study contributes to the literature in several ways. First, by applying time series analysis to historical coffee price data extending over 34 years, it provides empirically supported insights into the trends, patterns, and price volatility in global coffee markets. Unlike previous studies, this study provides updated forecasts through March 2028 using a selected SARIMA model. This analysis enhances coffee price forecasting, supporting production, investment, and risk management decisions (Janakiraman et al., 2025). Moreover, the study provides a baseline forecast that can be used as a benchmark for assessing more complex models integrating external variables such as supply chain factors and climate data. Finally, by integrating modern statistical tools with economic principles, this research shows that data-driven approaches can enhance understanding of market trends and facilitate more efficient pricing decisions (Makridakis et al., 2018).

2. LITERATURE REVIEW

Global coffee prices, especially for Arabica coffee, show significant volatility caused by a combination of supply- and demand-side factors, which include weather conditions in major producing countries, production quantity, trade disruptions, and global consumption patterns (International Coffee Organization, 2023; Massrie, 2025). Temperatures of 18–22°C and well-distributed annual rainfall of approximately 1,200–1,800 mm are optimal for Arabica coffee (*Coffea arabica*) for proper growth and high-quality yield (Scott, 2015). Deviations from these conditions can significantly reduce quality and yield, making Arabica coffee vulnerable to climate fluctuations (International Coffee Organization, 2023). Bunn et al. (2015) reported that changes in climatic suitability affect the global supply of coffee by altering the geographic distribution of coffee cultivation. Beyond climatic influences, biological factors also contribute to coffee production fluctuations. Avelino et al. (2015) reported that a coffee leaf rust epidemic in Central and South America between 2008 and 2013 caused significant production losses, directly impacting international coffee prices and highlighting the market's sensitivity to agricultural risks.

Global crises and macroeconomic shocks amplify volatility in coffee markets. Cantor (2023) highlights that global disruptions, such as the COVID-19 pandemic, affected coffee markets through impacts on labor availability, trade flows, and supply chains. As coffee is a commodity traded worldwide, exchange rate fluctuations also influence price trends and export potential (International Coffee Organization, 2023). Additionally, the International Coffee Organization (2023) reports that rising demand and changing consumption patterns, especially in emerging markets, play an important role in influencing price movements. The interaction between constrained supply and growing demand worsens market volatility. Structural drivers, including inflation and energy prices, indirectly affect coffee production and distribution costs, resulting in market price volatility (Massrie, 2025).

Given the complex interplay of these factors, forecasting of coffee prices is essential for rational decision-making. Time series forecasting models are commonly used to assess commodity price trends, particularly when the data exhibit seasonality and trend (Hyndman & Athanasopoulos, 2021). Several empirical studies have used time series models to project coffee prices. For example, Deina et al. (2022) used ARIMA and other forecasting frameworks for coffee price forecasting and found that Extreme Learning Machines (ELMs) achieved greater predictive accuracy. Janakiraman et al. (2025) contrasted ARIMA and SARIMA models with an LSTM-based hybrid approach for Indian coffee export forecasting and observed that the hybrid model attained greater predictive accuracy than machine learning and statistical models. Rahayu et al. (2015) applied ARCH/GARCH and EGARCH models to examine Indonesian coffee price fluctuations and found that international coffee prices showed varying effects on domestic coffee price returns.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model captures both recurring seasonal patterns and evolving trends, making it especially suitable for data exhibiting both characteristics (Box et al., 2015). Global coffee price series exhibit seasonal patterns driven by harvesting cycles and recurring supply changes, making SARIMA a suitable modeling framework. Model performance in such studies is typically evaluated by using statistical metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Akaike Information Criterion (AIC), which assess model adequacy and predictive accuracy (Box et al., 2015; Makridakis et al., 2018; Khadka & Chi, 2024). Time series models have been applied extensively in climate-related studies, including temperature and rainfall forecasting, in addition to commodity price forecasting, highlighting their adaptability in capturing both seasonal and non-seasonal fluctuations (Makridakis et al., 2018). Given the strong dependence of coffee production on climatic conditions, the integration of time series modeling in both environmental and economic contexts is relevant. Variation in climatic conditions, especially temperature and precipitation, has been shown to directly impact coffee yields and, consequently, price trends (Bunn et al., 2015).

Overall, the previous studies suggest that coffee price volatility arises from a complex interaction of economic, climatic, biological, and market-specific factors. Time series models, particularly SARIMA, provide a reliable framework for examining and predicting these patterns. Despite extensive research on coffee price forecasting, several research gaps remain. First, few studies have applied SARIMA modeling to the most recent data covering the recent supply chain disruptions and post-COVID period. Second, while multivariate models offer advantages, univariate SARIMA models remain valuable because of their interpretability, simplicity, and ability to provide baseline forecasts without requiring external explanatory variables. Third, there is a need for the latest forecasts to support current decision-making. This study fills these gaps by applying SARIMA modeling to monthly Arabica coffee price data from January 1992 to March 2026, generating forecasts through March 2028 using in-sample fit measures and residual diagnostic tests.

3. MATERIALS AND METHODS

3.1 Data

Monthly global Other Mild Arabica coffee prices, measured in U.S. cents per pound, were obtained from the International Monetary Fund through the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data (FRED) database. The analysis used the original price-level series before differencing. The series, identified as Global price of Coffee, Other Mild Arabica (PCOFFOTMUSDM), covers the period from January 1992 to March 2026 (International Monetary Fund, 2026). All analyses were conducted using R software V 4.5.2 for macOS.

3.2 Stationarity Testing

For ARIMA-type time series modeling, the series should be stationary after appropriate transformation, with a stable mean and variance over time and autocovariance that depends primarily on the lag rather than time. Non-stationary data, characterized by seasonality, trends, or dynamic variability, can produce spurious results if modeled without transformation (Hamilton, 1994; Box et al., 2015). Stationarity was assessed using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), which tests whether series contain a unit root (null hypothesis) indicating non-stationarity, against the alternative of stationarity. A $p\text{-value} \leq 0.05$ provides evidence against the unit-root null hypothesis and supports the conclusion that the series is stationary.

3.3 Data Transformation

To address non-stationarity, first-order differencing was applied:

$$\Delta y_t = y_t - y_{t-1}$$

Where Δ is the first difference operator, y_t is the value at time t , and y_{t-1} is the value at time $t-1$. First-order differencing was sufficient to achieve stationarity; therefore, second-order differencing was not applied.

$$\Delta^2 y_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$$

The order of differencing, denoted by d , determines the integration order of the ARIMA model. A stationary series that requires no differencing is represented as $I(0)$, whereas a series requiring first-order differencing is represented as $I(1)$ (Box et al., 2015). A stationary series without differencing is represented as $I(0)$ (Box et al., 2015).

3.4 SARIMA Modeling Framework

Within the Box-Jenkins modeling framework, the SARIMA model extends ARIMA by incorporating seasonal components to capture seasonal variation in time-series observations. The approach comprises three stages: (1) identification: determining model order based on autocorrelation (ACF) and partial autocorrelation (PACF) functions; (2) estimation: parameter estimation using maximum likelihood; and (3) diagnostic checking: testing residuals to verify model adequacy (Box et al., 2015).

The SARIMA model is represented as $SARIMA(p,d,q) (P,D,Q)[s]$

where,

p , d , q denote non-seasonal autoregressive, integrated (differencing), and moving average orders, respectively; P , D , Q denote seasonal counterparts of p , d , q ; and s denotes the seasonal period (12 months for monthly data).

3.5 Model Selection

Model selection followed a structured sequential approach. Candidate models were identified based on ACF and PACF patterns observed in the stationary time series. The `auto.arima()` function in R was then used to search across ARIMA and SARIMA specifications. The final model was selected based on the information criterion used by the procedure and was further evaluated using residual diagnostic tests to assess model

adequacy. The notation of the ARIMA model represents the order of the Autoregressive (AR), differencing (I), and Moving Average (MA) components, with their seasonal counterparts. Diagnostic tests, including the Ljung–Box test, were employed to verify that residuals showed no significant autocorrelation and behaved as a random noise process. This approach balanced model accuracy against complexity, ensuring a concise yet adequate model specification.

3.6 Justification for Univariate Approach

While multivariate models incorporating climate and supply variables may improve forecasting performance, this study uses a univariate SARIMA framework for three reasons. First, the model relies only on historical price data, which is readily available and consistently measured. Second, univariate models generate dependable baseline forecasts that can serve as benchmarks for more advanced multivariate model formulations. Third, the transparency and interpretability of SARIMA models make them easily understandable to stakeholders without specialized statistical training.

3.7 Model Evaluation

In-sample model fit was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Model adequacy was further assessed using residual diagnostics, including the Ljung–Box test for residual autocorrelation and graphical assessment of residual normality (Box et al., 2015; Makridakis et al., 2018).

4. RESULTS

The dataset consists of 411 monthly observations of the global Other Mild Arabica coffee price series. Summary statistics show an average monthly price of 153.14 cents per pound (SD = 72.64), with a minimum of 50.83, a maximum of 409.68, and a median value of 140.71 cents per pound. The time series plot (Figure 1) and its lag plot (Figure 2), recorded from January 1992 to March 2026, show fluctuations with some trends and patterns.

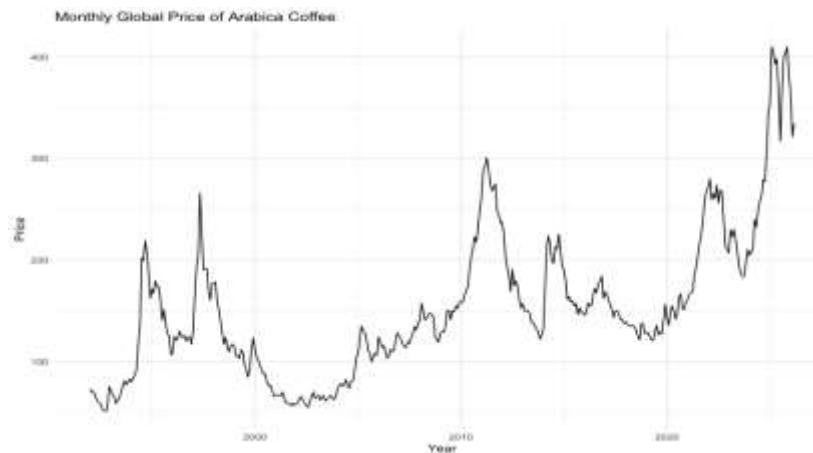


Figure 1: Time series plot of the monthly global Other Mild Arabica coffee price (January 1992–March 2026).
Source: Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

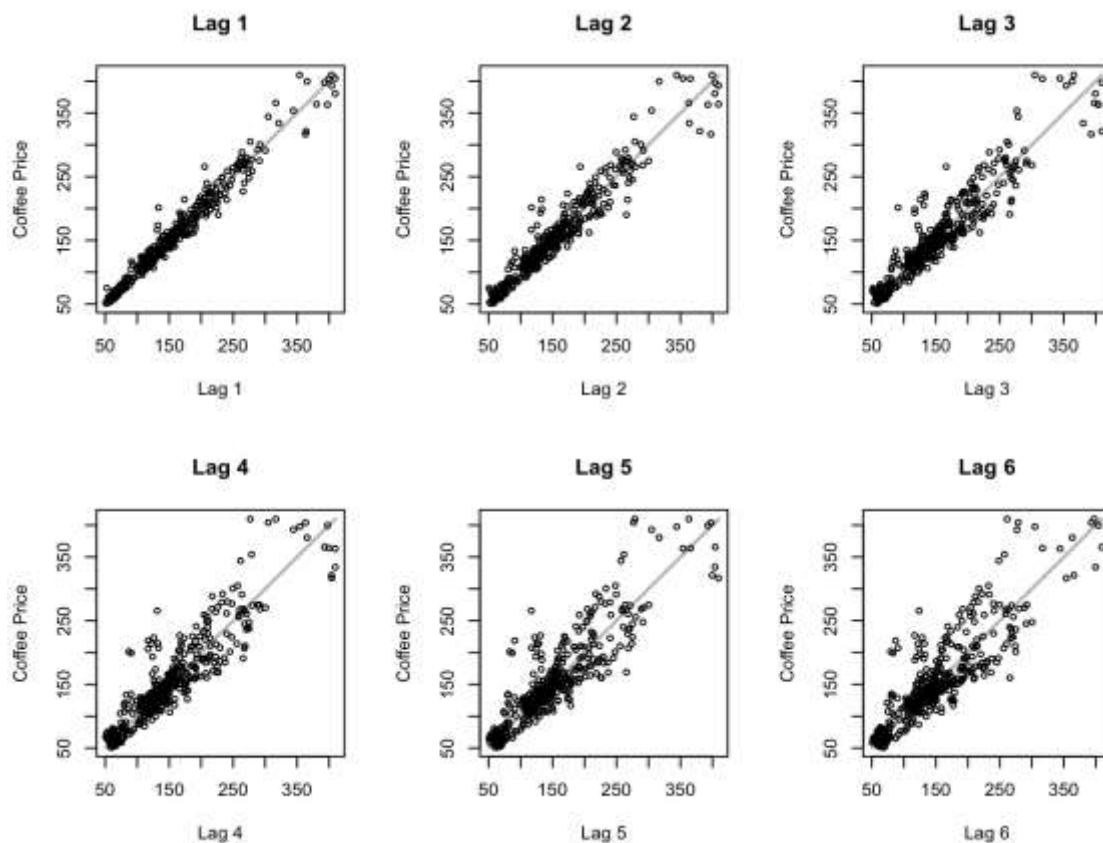


Figure 2: Lag plots of the monthly global Other Mild Arabica coffee price series (January 1992–March 2026).¹

¹ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

The lag plots indicate dependence between current and past price observations. Seasonal variations can be seen in prices, potentially influenced by harvest periods, weather events, and demand. The series exhibits substantial fluctuations, with a peak in 2011, a trough in 2019, another peak at the end of 2025, and a recent decline.

Stationarity of the original series was assessed using the Augmented Dickey–Fuller (ADF) test. The ADF statistic was -2.864 , with a p-value of 0.2124 , which is greater than 0.05 ; therefore, the null hypothesis of a unit root could not be rejected, indicating that the series was non-stationary. To examine the dependence structure of the series and inform model selection, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were analyzed. A gradual decay is evident in the ACF plot (Figure 3), aligning with an autoregressive pattern. The PACF plot (Figure 4) exhibits a strong spike at lag 1 followed by smaller values at subsequent lags, suggesting that a low-order autoregressive component may be appropriate.

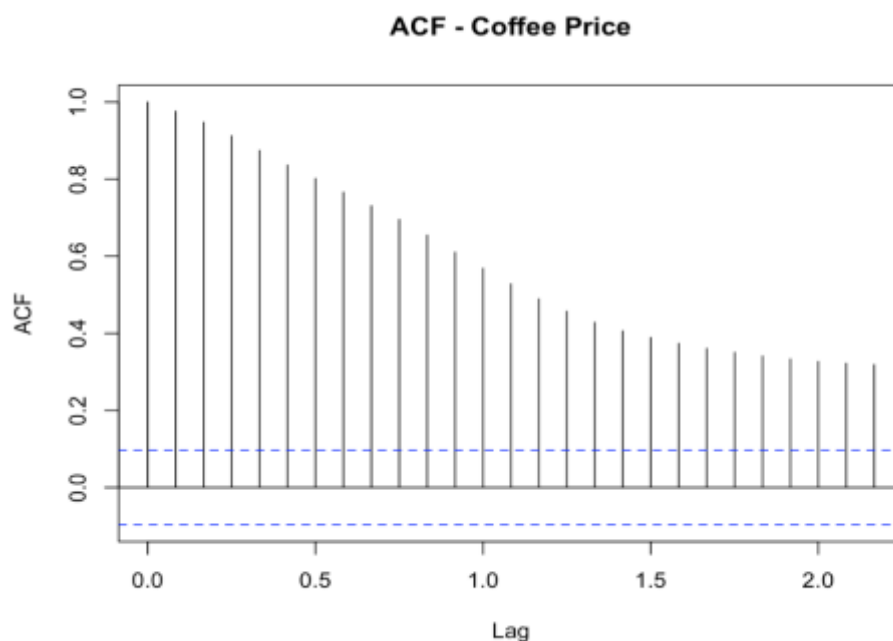


Figure 3: ACF plot of the monthly global Other Mild Arabica coffee price (January 1992–March 2026).²

² **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

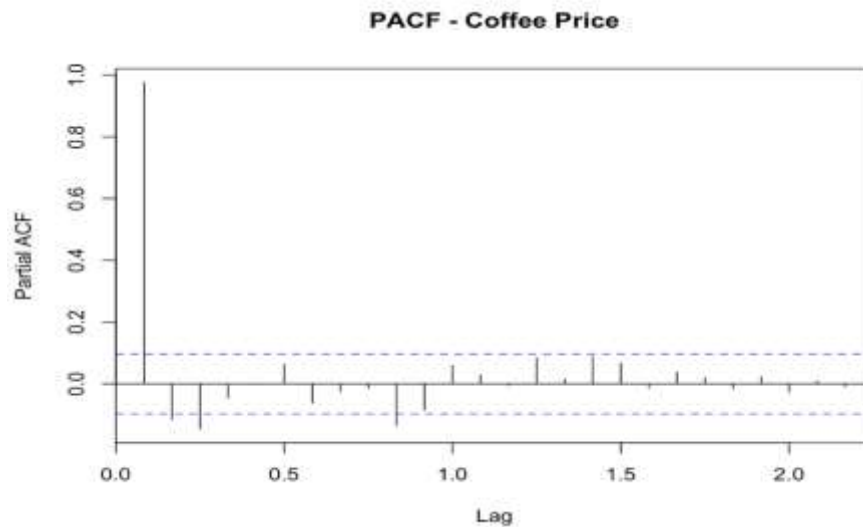


Figure 4: PACF plot of the monthly global Other Mild Arabica coffee price (January 1992–March 2026).³

To further examine the sources of non-stationarity and confirm the presence of systematic patterns, the series was decomposed into trend, seasonal, and remainder components (Figure 5). The findings indicate a stable seasonal pattern over time, while the remainder shows relatively constant variability. Seasonal decomposition was used to examine the underlying trend and seasonal structure of the series. Although the estimated seasonal component was relatively small, evidence of seasonal dependence remained. Therefore, the original series was first differenced to achieve stationarity and subsequently modeled using the SARIMA framework.

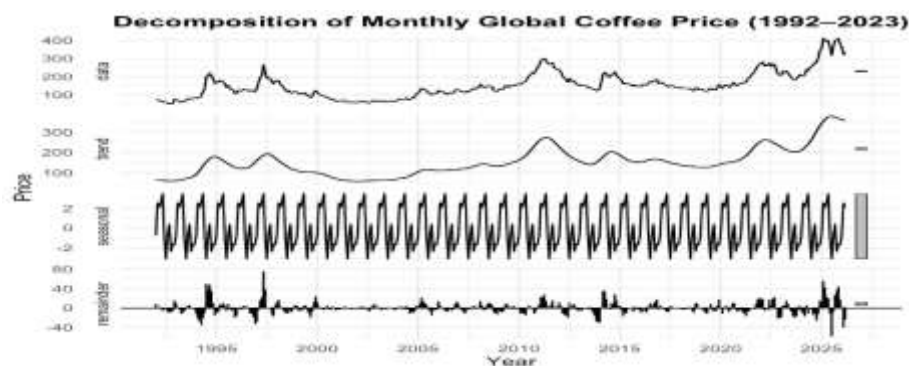


Figure 5: Decomposition of the monthly global Other Mild Arabica coffee price (January 1992 - March 2026).⁴

³ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

⁴ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

Although the estimated seasonal component was relatively small, some seasonal dependence remained. Therefore, seasonal terms were considered during model identification. The original series was first-differenced to address non-stationarity, and the resulting series was used for SARIMA model identification and estimation.

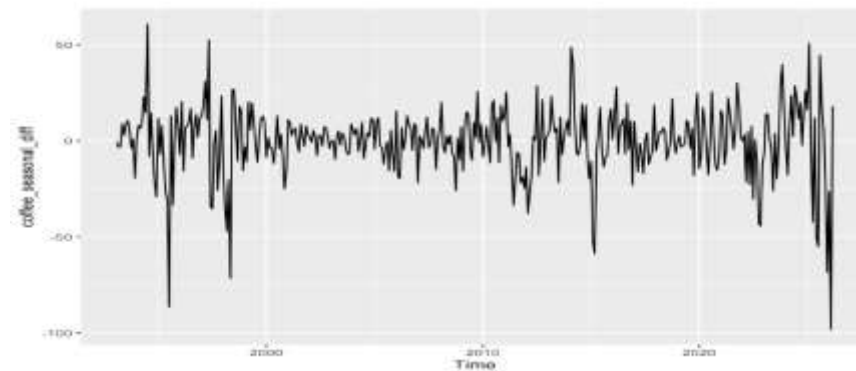


Figure 6: Time series plot of the first-differenced monthly global Other Mild Arabica coffee price (January 1992 - March 2026).⁵

The ADF test on the differenced series gave a test statistic of -5.6243 with a p-value of 0.01, which is less than the significance level $\alpha = 0.05$, supporting the conclusion that the series is stationary. The transformation successfully removed the non-stationary trend, making the data appropriate for subsequent SARIMA modeling. The underlying correlation structure of the first-differenced series was examined through ACF and PACF plots (Figures 7 and 8).

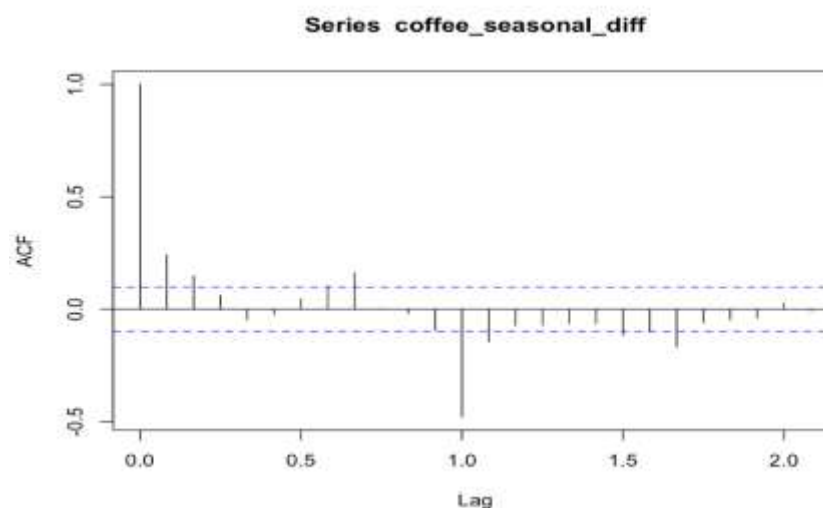


Figure 7: ACF plot of the first-differenced monthly global Other Mild Arabica coffee price (January 1992 - March 2026).⁶

⁵ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

⁶ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

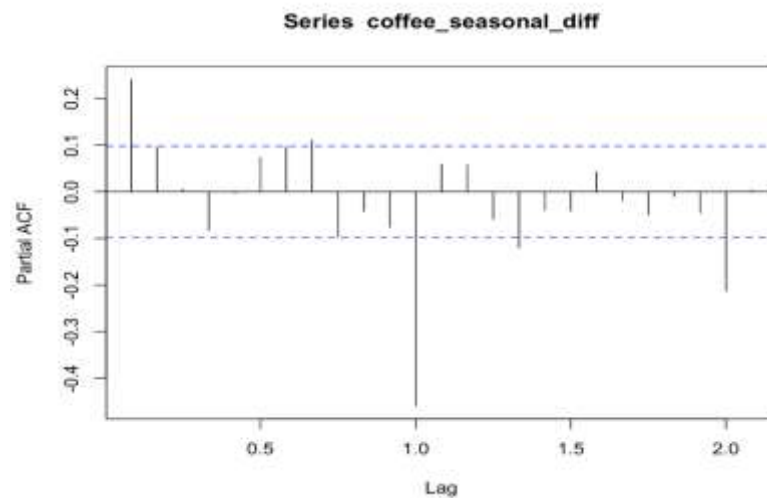


Figure 8: PACF plot of the first-differenced monthly global Other Mild Arabica coffee price (January 1992 - March 2026).⁷

The ACF plot shows weak short-term persistence in the series, with a significant spike at lag 1, followed by a rapid decline toward zero. A noticeable spike around the seasonal lag suggests residual seasonal effects may still be present. The PACF plot does not exhibit a clear cutoff pattern, but rather small and scattered spikes, indicating no strong higher-order autoregressive structure. Overall, the patterns indicate that a low-order ARIMA specification may be suitable, with limited AR and MA terms.

Among the candidate models evaluated by the `auto.arima()` procedure, the $SARIMA(2,1,2)(1,0,0)[12]$ specification was selected based on its lowest AIC value and satisfactory residual diagnostics. With an AIC of 3211.7, this model provided the best balance between fit and complexity. The non-seasonal part of the model includes two autoregressive (AR) terms and two moving-average (MA) terms, with first-order differencing (I) to achieve stationarity. The seasonal component includes a first-order seasonal autoregressive term with 12 months, capturing yearly patterns in the coffee price series. Table 1 illustrates the estimated Parameters of the $SARIMA(2,1,2)(1,0,0)[12]$ Model for the coffee price series.

⁷ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

Table 1*Parameters of the SARIMA(2,1,2)(1,0,0)[12] Model⁸*

Parameter	Estimate	Standard Error
AR1	0.99	0.06
AR2	-0.84	0.07
MA1	-0.86	0.06
MA2	0.86	0.07
SAR1	-0.09	0.05

 $\sigma^2 = 145$

Log Likelihood = -1599.85

AIC = 3211.7, AICc = 3211.91, BIC = 3235.8

RMSE = 11.95, MAE = 8.2, MAPE = 5.37

The autoregressive coefficients (AR1 = 0.99, AR2 = -0.84) indicate dependence on previous values of the differenced price series. The positive AR1 and negative AR2 coefficients jointly describe the short-run dynamic structure of the differenced series. The moving average terms (MA1 = -0.86 and MA2 = 0.86) show that past model errors continue to affect current values. The seasonal autoregressive coefficient was relatively small (SAR1 = -0.09), suggesting limited seasonal autoregressive dependence at the 12-month lag.

The estimated error variance ($\sigma^2 = 145$) represents the remaining unexplained variation after fitting the model. The log-likelihood value (-1599.85) measures model fit; the log-likelihood contributes to the information criteria used for model comparison. Lower values generally indicate a preferred model among competing specifications, all else being equal. Finally, the in-sample error measures (RMSE = 11.95, MAE = 8.20, MAPE = 5.37%) indicate the closeness of the fitted values to the observed series, with lower values indicating better in-sample fit. These measures should not be interpreted as out-of-sample forecasting accuracy.

⁸ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

Residual Analysis and Model Verification

The residual diagnostics (Figure 9) assessed the adequacy of the fitted SARIMA (2,1,2)(1,0,0)[12] model.

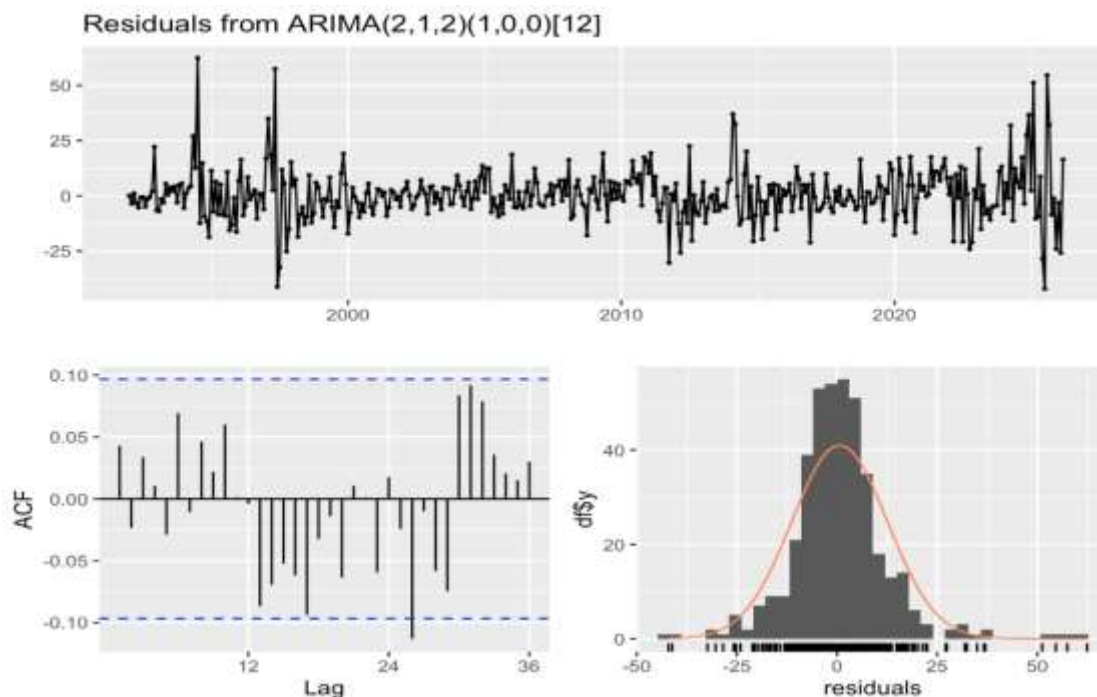


Figure 9: Residual diagnostics of the SARIMA(2,1,2)(1,0,0)[12] model: standardized residuals, residual autocorrelation function (ACF), and histogram with normal distribution curve (January 1992 - March 2026).⁹

The standardized residuals fluctuate randomly around zero with no clear systematic pattern. The ACF plot of the residuals (Figure 9, bottom left) suggests no significant autocorrelation at most lags, suggesting that the model has successfully captured the main structure in the data. The histogram (Figure 9, bottom right) implies that the residuals are approximately normally distributed. The Ljung–Box test produced p-values of 0.27 and 0.42 at the specified lag lengths, both exceeding the 5% significance level. This suggests no significant autocorrelation in the residuals. Overall, the results in Figure 9 provide no evidence of substantial remaining serial correlation in the residuals and support the adequacy of the fitted model.

⁹ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

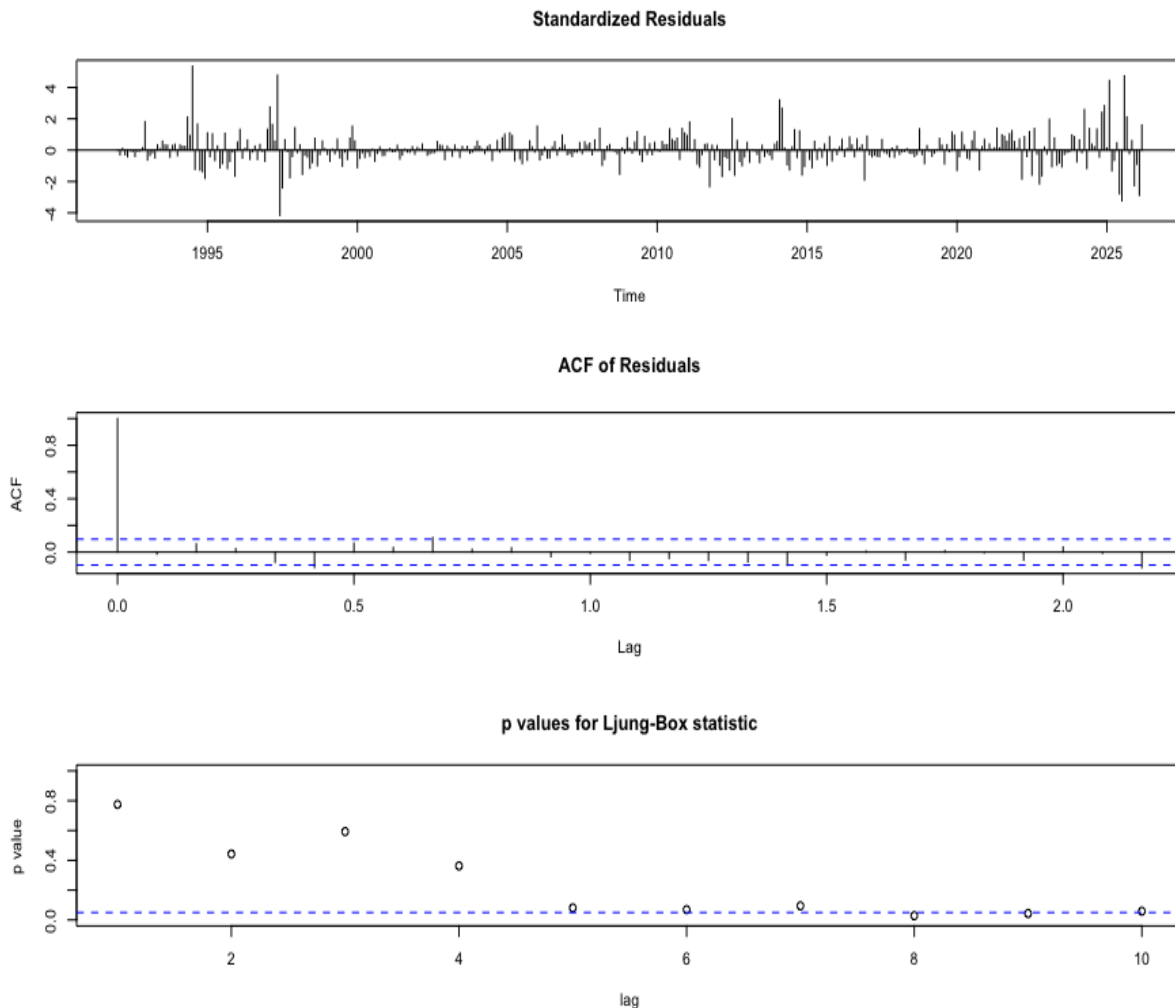


Figure 10: Normal Q-Q plot of the residuals from the SARIMA(2,1,2)(1,0,0)[12] model for monthly global Other Mild Arabica coffee prices (January 1992–March 2026).¹⁰

Normality of the model residuals was assessed using the Q-Q plot (Figure 10). The residuals lie reasonably close to the reference line, indicating approximate normality with no strong skewness or extreme deviations. Combined with the residual autocorrelation diagnostics and Ljung–Box test results, these findings indicate that the SARIMA(2,1,2)(1,0,0)[12] model is diagnostically adequate for the coffee price series.

¹⁰ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

Forecasting Results

Global coffee price forecasts from April 2026 to March 2028 were made using the fitted SARIMA model, and the forecast values were visualized (Figures 11 and 12).

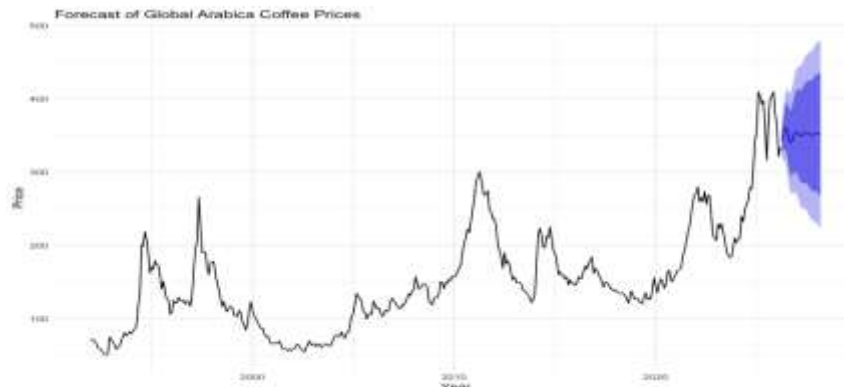


Figure 11: Forecasted monthly global Other Mild Arabica coffee price under upper and lower confidence levels (April 2026-March 2028).¹¹

Figure 12 illustrates the observed price (dotted line) and fitted values (solid line) from the same SARIMA model of the monthly global coffee prices from January 1992 to March 2026. The fitted values closely follow the actual price, capturing the overall trend well, with small deviations due to short-term fluctuations.



Figure 12: Observed and fitted monthly global Other Mild Arabica coffee prices (January 1992–March 2026).¹²

¹¹ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

¹² **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

The forecast results suggest that Other Mild Arabica coffee prices may increase during the initial months of the forecast period, reaching relatively higher levels around mid-2026. After this, the series exhibits moderate fluctuations with both upward and downward movements. Overall, the point forecasts remain relatively stable after the initial forecast period, although prediction intervals widen substantially over the longer forecast horizon. The prediction intervals associated with the forecasts widen gradually over time, indicating increasing uncertainty as the forecast horizon extends further into the future. Despite this, the central forecast values remain stable, indicating that the model provides a transparent baseline framework for the underlying structure of the data. The detailed monthly forecast values, along with their confidence intervals, are presented in Table 2.

While these in-sample diagnostics confirm model adequacy, the evaluation metrics are derived from the same dataset used for estimating the model. Future research could strengthen these results using out-of-sample validation through hold-out sample validation or rolling forecast evaluation.

Table 2

Forecast monthly global Other Mild Arabica coffee price with 80% and 95% Confidence Intervals (April 2026 – March 2028)¹³

Month	Point Forecast	Lower 80% CI	Upper 80% CI	Lower 95% CI	Upper 95% CI
Apr 2026	342.33	326.90	357.77	318.73	365.94
May 2026	352.93	329.80	376.07	317.55	388.31
Jun 2026	360.72	330.55	390.89	314.58	406.86
Jul 2026	360.20	324.03	396.36	304.89	415.51
Aug 2026	347.29	306.57	388.01	285.01	409.56
Sep 2026	339.75	295.62	383.88	272.26	407.24
Oct 2026	342.16	295.09	389.23	270.17	414.14
Nov 2026	348.21	298.11	398.32	271.58	424.85
Dec 2026	354.94	301.51	408.36	273.23	436.64
Jan 2027	354.91	298.16	411.66	268.11	441.70
Feb 2027	353.71	293.98	413.45	262.35	445.07
Mar 2027	348.95	286.67	411.23	253.70	444.20
Apr 2027	348.84	284.62	413.06	250.63	447.05
May 2027	351.58	285.45	417.71	250.44	452.71
Jun 2027	353.99	285.86	422.12	249.79	458.19
Jul 2027	353.99	283.80	424.18	246.65	461.33
Aug 2027	352.46	280.28	424.64	242.07	462.85
Sep 2027	350.53	276.52	424.55	237.34	463.73
Oct 2027	350.02	274.30	425.75	234.22	465.83
Nov 2027	351.39	274.00	428.78	233.03	469.74
Dec 2027	352.92	273.83	432.00	231.97	473.86
Jan 2028	353.41	272.60	434.21	229.82	476.99
Feb 2028	352.20	269.69	434.71	226.01	478.38
Mar 2028	350.91	266.78	435.04	222.24	479.58

¹³ **Source:** Authors' computation based on International Monetary Fund data retrieved from FRED, Federal Reserve Bank of St. Louis (January 1992–March 2026).

5. DISCUSSION

The empirical results of this study show that global Other Mild Arabica coffee prices exhibit short-term fluctuations and some recurring seasonal dependence over the period analyzed. The SARIMA(2,1,2)(1,0,0)[12] model was able to adequately capture these dynamics, as evidenced by both in-sample fitting performance and diagnostic checks. These findings suggest that past price movements alone provide useful information for short- to medium-term forecasting. Residual diagnostics further confirm the adequacy of the selected SARIMA model. The standardized residuals vary randomly around zero with no clear pattern, suggesting that the model has properly captured the systematic components of the data. Moreover, the autocorrelation function of the residuals shows no significant remaining correlations at most lags, and the Ljung–Box test produced p-values above the 5% significance level. These results collectively indicate that the residuals behave like white noise (Box et al., 2015).

The favorable diagnostic results indicate that the SARIMA model has effectively extracted both the short-term dependence structure and the seasonal effects in the data. In particular, the inclusion of a seasonal autoregressive term helps account for potential recurring yearly patterns, which are commonly observed in agricultural commodity prices due to cyclical production and market behavior (Box et al., 2015; Hyndman & Athanasopoulos, 2021). At the same time, the non-seasonal AR and MA components capture short-run adjustments and shocks in the time series.

The forecasting results suggest the projected future behavior of coffee prices. The projected values from April 2026 to March 2028 show relatively stable point forecasts with moderate month-to-month fluctuations rather than a strong directional trend. This suggests that, based on historical patterns, the coffee market is not expected to show extreme instability in the short-to-medium term. However, the gradual widening of confidence intervals highlights rising uncertainty as the forecast horizon extends, which is a common feature in time series forecasting and reflects the reduced reliability of long-term predictions (Hyndman & Athanasopoulos, 2021). These results are particularly valuable for stakeholders such as farmers, exporters, traders, and policymakers, who rely on price expectations for planning production, managing inventory, and making financial decisions. The model-based forecasts may therefore provide a useful baseline for risk assessment and decision-making in the coffee value chain.

However, the results also indicate that forecast uncertainty increases significantly over time, raising the risk of relying solely on univariate historical models for long-term prediction. As the SARIMA model is based only on past price behavior, it cannot clearly account for external shocks or structural changes that may arise from unexpected global events (Makridakis et al., 2018). This highlights the importance of

interpreting long-term forecasts with caution in commodity markets that are highly sensitive to external influences. Overall, the findings show that the SARIMA model is effective for modeling and forecasting coffee price dynamics. However, forecasting performance could be further improved by integrating external variables or more advanced methods.

Several limitations should be considered. First, the SARIMA model is univariate and does not directly incorporate production data, climate variables, or supply-side factors. While these factors are discussed within the context of coffee market volatility, the model itself relies exclusively on historical price movements to generate forecasts. Second, the forecast uncertainty increases considerably over the forecast horizon, reflecting the inherent uncertainty of commodity markets. Third, the study's focus on univariate modeling means that structural shifts or regime changes may not be fully captured. These limitations suggest that the model should be interpreted primarily as a baseline forecasting tool, particularly as the forecast horizon becomes longer and prediction uncertainty increases.

Future research could extend the scope of this analysis in several directions. Incorporating external variables such as production data, climate indicators, and exchange rates into a multivariate modelling framework could provide potentially more accurate forecasts. Additionally, comparing SARIMA performance against alternative approaches, including ARIMAX, ETS, VAR, and machine learning methods, would help identify the most suitable modeling approaches for different forecasting horizons and market conditions. Finally, scenario-based forecasting that simulates the impact of policy changes, climate change, or global demand fluctuations could provide stakeholders with a more comprehensive range of possible future outcomes.

6. CONCLUSION

This study applied the Box-Jenkins approach to develop a model and generate forecasts of global Other Mild Arabica coffee prices using monthly data from January 1992 to March 2026. We selected the SARIMA(2,1,2)(1,0,0)[12] model based on information criteria and residual diagnostics and found a satisfactory in-sample fit with no significant residual autocorrelation. Forecasts through March 2028 showed relatively limited fluctuations in the point forecasts, while prediction uncertainty increased substantially over time, as reflected by widening prediction intervals.

These findings suggest that SARIMA provides a useful baseline framework for modeling and forecasting coffee price dynamics. The results may provide practical value for policymakers, farmers, traders, and other market participants by providing a baseline indication of possible future price movements. However, when interpreting the results, the study's reliance on univariate modeling and the absence of direct climate or

supply variables should be considered. Future research could extend this analysis by incorporating external variables and alternative modeling methods. Despite these limitations, this study provides a useful baseline forecast that may support planning and risk assessment in the global Other Mild Arabica coffee market.

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CONFLICT OF INTEREST

The authors declare that they have no known conflicts of interest or financial or personal relationships that could have influenced the work reported in this manuscript.

GENERATIVE AI DISCLOSURE

The authors confirm that generative AI was used only for language editing and formatting help in the preparation of this manuscript. No generative AI tools were used for research design, data collection, data analysis, results interpretation, or reference generation. All AI-assisted content has been reviewed and approved by the authors, and AI tools are not listed as co-authors in compliance with IJBE policy.

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