Modeling and Forecasting Coconut Oil Prices Using Time Series Data Analysis Based on Box-Jenkins Methodology

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Abstract

Coconut oil is a significant global commodity, ranking 4th most valuable after palm oil. Its rising demand and market volatility have heightened the need for accurate price forecasting to guide investment decisions. This study uses the Box-Jenkins methodology to develop a prediction model for coconut oil prices. Monthly secondary data from the World Bank, covering January 1960 to March 2024, was analysed using R software. A Box-Cox transformation was applied to stabilize variance and address issues such as non-normality and heteroscedasticity in the data. After testing various ARIMA models, the ARIMA (0,1,0) model was identified as the most suitable for forecasting, with a MAPE of 27%, suggesting reasonable accuracy. The model provides a reliable tool for predicting future price trends. These findings are critical for industry stakeholders, enabling more informed decision-making and strategic planning by offering a clearer understanding of price fluctuations in the coconut oil market. This analysis contributes to optimizing investments and managing risks in a dynamic market environment.

Keywords : *ARIMA; Box-Jenkins; Coconut Oil; Forecasting; Predictive Model*

I. INTRODUCTION

Coconut oil is a vital agricultural commodity, widely utilized in various industries, including food, cosmetics, and pharmaceuticals. In recent decades, the coconut industry has seen a significant rise in production and demand for coconut-based products, contributing significantly to producer countries' economies [1]. Coconut oil is an important product, and it is ranked as the 4th most important commodity, following palm oil. The coconut oil generated income to Malaysia of around RM70.1mil in 2018 [2]. However, this particular product has its pitfalls due to competition with other consumers' products, such as palm oil, corn oil, and other oils. The coconut oil exports decreased starting from 2014 to 2019 by 4.46%, and imports increased by 31.1%. In Malaysia, the demand for products made from coconut increases every year. The oldest industrial crop in Malaysia made a significant contribution of RM72.8 million, accounting for 0.06% of the country's agricultural export earnings in 2020 [3]. Malaysia exported coconut-based goods in 2020, including fresh coconuts, dried coconut, activated carbon, and charcoal [4] Table 1 displays the export values of various coconut-based products, totaling RM 5698.75 million. Coconut oil holds the highest export value at RM 3395.81 million, followed by coconut milk and activated carbon.

Table 1 Export value in detail of coconut-based products

Coconut Based Products	Value (RM Million)
Coconut oil	3395.81
Coconut milk	655.12
Activated carbon	609.63
Coconut charcoal	503.11
Processed coconut water	234.69
Desiccated coconut	173.75
Coconut fibre	77.46
Fresh coconut	49.16
Total	5698.75

Source: UN Contrade [5]

Table 2 presents data on coconut production and the corresponding coverage areas across various nations. According to Table 2, the largest coconut

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production is Indonesia, with a coverage area of approximately 2,800,000 hectares, and the second largest is dominated by the Philippines, followed by India and Sri Lanka. In addition, Malaysia's coconut production is currently ranked 10th, encompassing about 86,446 hectares of land. Malaysia produces approximately 536 606 mt of coconuts per year, but this is not enough to meet the demand since the country's total consumption is 745,657.1 mt a year. The gap between these figures is large, requiring Malaysia to import coconuts from other countries like Indonesia and the Philippines.

Table 2 Coconut production and coverage areas based on nations

Rank	Country	Production (tonnes)	Hectares
1	Indonesia	17,128,595	2,800,000
2	Philippines	14,765,057	3,651,873
3	India	14,682,000	2,151,000
4	Sri Lanka	2,468,800	503,452
5	Brazil	2,330,949	186,950
6	Vietnam	1,677,044	158,959
7	Mexico	1,287,957	204,133
8	Papua New Guinea	1,192,816	188,841
9	Thailand	806,026	124,374
10	Malaysia	536,606	86,466
11	Myanmar	530,832	48,902
12	Bangladesh	431,596	36,483
13	United Republic of Tanzania	428,595	657,658
14	Dominican Republic	421,559	52,031
15	Others	4,186,784	1,005,306
Total		62,875,216	11,856,428

Source: UN Contrade [2]

There is a growing demand for coconut oil in Malaysia, but the supply is insufficient. Fluctuating consumption and production levels present opportunities for businesses interested in coconut products. The current trend shows significant potential for growth in the coconut oil market [6]. However, the volatility of coconut oil prices and its varying profitability make it crucial to develop models and forecasts to gain insight into these issues. This research aims to develop a prediction model for coconut oil prices using Box-Jenkins time series data analysis in the Malaysian market and evaluate its efficiency in forecasting coconut oil prices from April 2024 to December 2024.

The ARIMA model in the Box-Jenkins approach is well-suited for handling non-stationary agricultural commodity price data. The analysis findings will contribute to agricultural price forecasting knowledge and offer practical insights for coconut oil market stakeholders. This study seeks to enhance coconut oil price forecasts by analysing time series properties and applying rigorous model validation techniques to support more informed decision-making in the industry.

II. LITERATURE REVIEW

Exploring various econometric and statistical methods to analyse and forecast coconut oil prices in different markets reveals multiple modeling techniques. Many studies related to the coconut sector have applied similar modeling approaches. ARIMA (1,2,1) has been identified as the most adequate and efficient model to forecast coconut oil prices in the Cochin market [7] The study conducted in Sri Lanka concluded that the NARX model, which includes coconut production as an exogenous variable, was the most effective nonlinear time series model for accurately forecasting coconut oil prices, surpassing the performance of the GARCH model [8]. The Intelligent Hybrid ARIMA with Nonlinear Autoregressive Neural Networks (NARNET) model effectively forecasts coconut prices, aiding farmers, exporters, and the government in maximizing profits by predicting future coconut prices accurately to overcome the inability of ARIMA model to handle non-linear patterns inherent in the price data [9] The study identifies Grey Forecasting as the most accurate method for predicting significant increases in coconut oil production from 2023 to 2025, aiding agricultural planning in the Philippines[10]. The VECM analyses the relationship between coconut oil and crude oil prices, revealing cointegration

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between the two commodities and highlighting stable equilibrium relationships and robust short-term adjustment mechanisms [11] Machine learning techniques like Support Vector Regression (SVR) and multi-layer perception models are used to forecast multivariate time series, predicting coconut oil prices alongside related commodities such as palm oil. These models analyse oil price correlations to provide more accurate forecasts by considering market interdependencies [12]. Recent advances in forecasting coconut oil prices have progressed beyond traditional models to include more complex and dynamic factors. Integrating machine learning techniques, hybrid models, and a broader systems approach has enhanced the accuracy of these forecasts, making them more dependable for stakeholders in the coconut oil industry.

III. RESEARCH METHODOLOGY

1) Data Description

The research employs a comprehensive historical monthly dataset of coconut oil prices obtained from the World Bank database. The data consists of weekly 771 observations from January 1960 to March 2024. The response variable is the market price of coconut oil measured in US Dollars per metric tonne (USD/mt). The analysis was done using R software.

2) Materials and Methods

a) Stationarity test

Time series data usually contain unit roots or are non-stationary in nature, especially for econometric datasets (ref). Time series data is said to be stationary if its mean and variance remain the same over time. If they change with some trend or pattern over time, then the time series is non-stationary in both mean and variance. Transformation is needed to make the data series stationary in variance, while differencing must be employed to make the data series stationary in mean.

One of the methods to identify the existence of unit roots is by using the Augmented Dickey-Fuller (ADF) test. The hypothesis of the model is represented as follows:

H_O: The time series is non-stationary
H_1: The time series is stationary

The time series is said to be stationary; if the p-value<0.05, the null hypothesis will be rejected.

b) Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) is a powerful method developed by Box and Jenkins, widely used in time series modeling and forecasting for non-stationary time series data. The ARIMA(p,d,q) model comprises autoregressive (AR), differencing (I), and moving average (MA) components, which are used in the order of p, d, and q. A general form of the ARIMA model using a backshift operator and difference form is given by Equation 1:

$$\varphi_P(B)\nabla^d y_t = c + \theta_q(B)a_t \ldots\ldots\ldots \textbf{Equation 1}$$

p: the order of AR model
q: the order of MA model
d: the order of differencing
B: backshift operator, $B^k y_t = y_{t-k}$
∇: difference operator, $\nabla^d = (1-B)^d$

c) Box-Jenkins Methodology

The Box-Jenkins method is a systematic approach to time series forecasting, which involves three main stages: model identification, parameter estimation, diagnostic checking, and forecasting. In the identification stage, the data is made stationary, and the orders of AR, I, and MA components are determined using ACF and PACF plots. After identifying the suitable ARIMA (p,d,q) model, the next stage is to estimate the parameters of the included autoregressive and moving average components. The selected model undergoes a diagnostic checking stage where the residual series of the chosen model is investigated to check the model adequacy. The adequate model is the model which has white noise error. The white noise errors in time series refer to the residuals with zero mean and constant variance and are serially uncorrelated. The common test used to detect the presence of autocorrelation is the Ljung Box (LBQ) test on residuals. The hypothesis test is as follows:

H_O: There is no remaining serial correlation in the residuals
H_1: There is a remaining serial correlation in the residuals

Failure to reject H_0 means that there is no serial correlation in the residuals. The residuals' autocorrelation (ACF) function and partial autocorrelation (PACF) function can be used in

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other ways than a statistical test. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the residuals should show that all autocorrelations are near zero, indicating no significant autocorrelation. The last stage in the Box-Jenkins method refers to forecasting.

Once a satisfactory model has been developed, it can be utilized to make forecasts. The simplified Box-Jenkins Model procedure is simplified in Figure 1 for non-seasonal datasets.

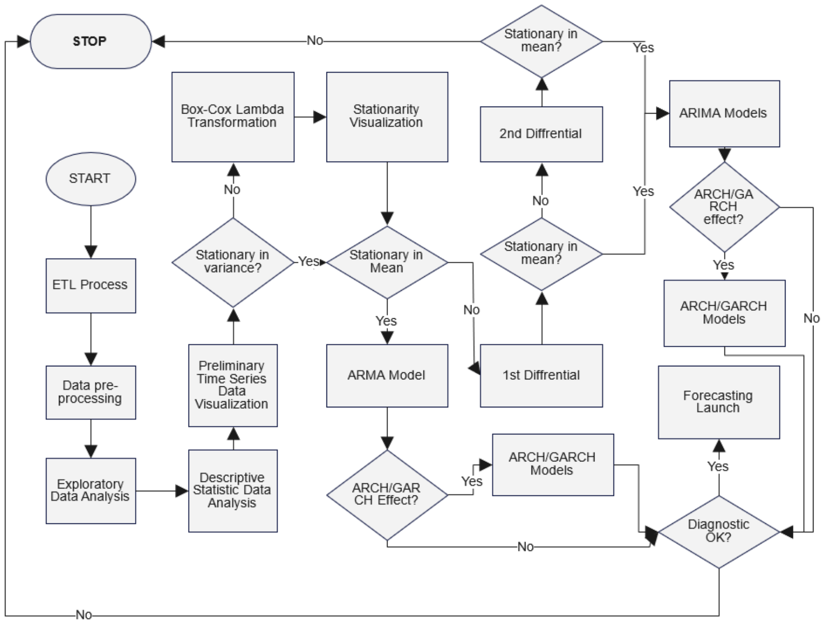

Figure 1 Box-Jenkins Methodology for Non-Seasonal Time Series Analysis and Forecasting

IV. RESULTS AND DISCUSSION

A preliminary analysis has been done to analyse the pattern of the time series dataset. The data are split into in-sample and out-of-sample datasets based on a ratio of 80:20. In-sample data are used to estimate the model and out-of-sample data are used to forecast coconut oil prices. Figure 2 presents monthly time series data plotting coconut oil prices from 1960 to 2024. Figure 2 illustrates both upward and downward trend patterns.

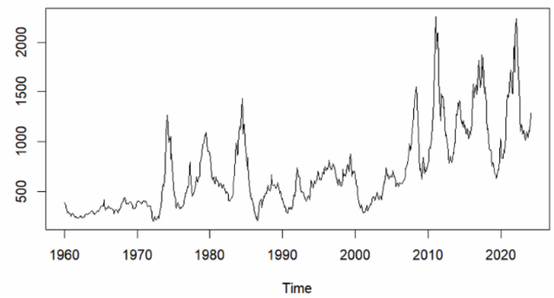

Figure 2 Time series data plotting for coconut oil prices

However, the predominant trend is upward, indicating an increase in the prices of coconut oil over time. Based on this trend, it is evident that the dataset does not exhibit a constant variance, as the the fluctuating pattern is inconsistent. Additionally, the dataset does not show a constant mean, as the price of coconuts remains the same over time. Therefore, ensuring the dataset is stationary is necessary to meet the Box-Jenkins method requirement. The preliminary analysis reveals small seasonality and a random pattern, indicating that the time series data is not stationary in mean and variance. Figure 3 shows the ACF and PACF visualizations for stationarity visualization based on the original dataset.

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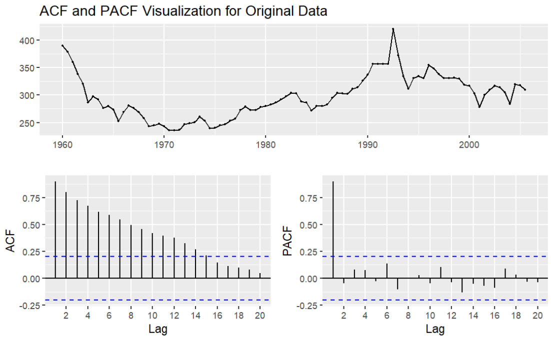

Figure 3 ACF and PACF for stationarity analysis and evaluation (Original data)

According to Figure 3, the data is slightly not stationary in variance and mean. Hence, data transformation using Box-Cox Lambda is preferred. The ACF and PACF are displayed in Figure 4 using transformed data. Figure 4 shows that the data is not stationary in mean, as the peak gradually decreases rather than suddenly reducing to zero.

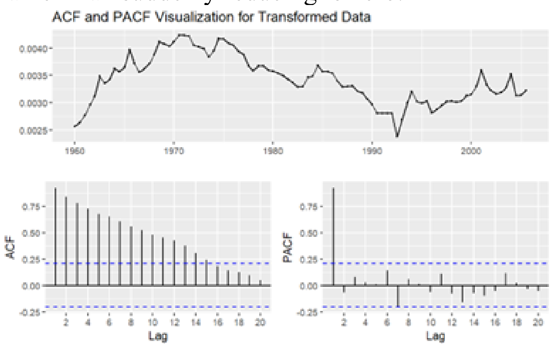

Figure 4 ACF and PACF for stationarity analysis and evaluation (Transformed data)

Thus, the first differential is required based on this equation, $Yd = Y_t - Y_{t-1}(diff[Y_t])$. On the other hand, this transformed data requires stationarity in the seasonal dataset. Hence seasonality stationarity will be conducted according to Equation 2:

$$y_s = diff(diff(Y_t, lag = 12), lag = 1)$$ **Equation 2**

The ADF unit root tests were used to check the dataset's stationarity. The results of the unit root test from the original data, the first difference form and second difference form of coconut oil prices, are summarised in Table 3. According to the ADF test for all stages of data stationarity, as shown in Table 3, the data is suitable for modeling and forecasting purposes.

Table 3 Augmented Dickey-Fuller (ADF) test for unit root

Coconut oil prices	Test statistic	p-value
Original data	-2.6414	0.3068
First difference	-6.9407	0.01
Second difference	-13.438	0.01

In the case of real data, the p-value was greater than a 5% significance level. Hence, the null hypothesis of non-stationary was not rejected. Therefore, the transformation is necessary to make the time series data stationary. The first and second differencing of the time series variable was found to be significant at a 5% significance level, confirming their stationarity. Figure 5 presents the ACF and PACF for stationarity analysis and evaluation (seasonal). Based on Figure 5 shows the seasonal data is stationed since peaks in ACF and PACF suddenly drop to zero. Hence, the parameter estimation for seasonal data is equal to $(P = 0, D = 2, Q = 0)$. Thus, the possible models for seasonal data are (0,0,0), (0,1,0), and (0,2,0). The possible SARIMA model starts with SARIMA $(0,1,0)(0,2,0)_{12}$. Since $p - value = 0.01 < 0.05$, reject H_0. Hence, at $\alpha = 0.05$, the data is stationary.

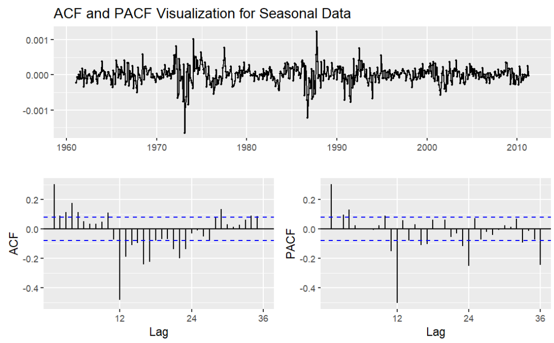

Figure 5 ACF and PACF for stationarity analysis and evaluation (seasonal)

Figure 6 displays the first differential dataset's ACF and PACF stationarity visualization. The data exhibits complete stationarity, as all the peaks suddenly drop to zero. Hence, the model parameter is equal to, and the possible models for non-seasonal are (0,1, 1) and (0, 0, 0). The data shows that coconut oil prices are stationary when considering the first and second differentials.

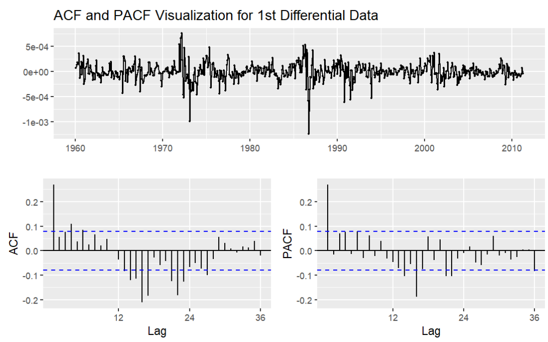

Figure 6 ACF and PACF for stationarity analysis

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and evaluation (1st differential)

Table 4 presents the list of significance possible models. According to Box-Jenkins, the best model is the model that follows the parsimony principle with the lowest Akaike Information (AIC) and Bayesian Information Criterion (BIC) values. Table 4 shows that among the ARIMA models, ARIMA (0,1,0) demonstrated a low AIC of 6693.07 and a BIC of 6697.5. The model is significant at a 5% level. The ARIMA (0,1,0) model was used to proceed with stage 3 of Box-Jenkins, which is diagnostic checking. The Ljung Box test was used to determine the best-fitted model. Since the p-value is 0.8868, the result does not reject H_0 as greater than 5%, indicating the residuals are serially uncorrelated.

Table 4 The list of possible significant models

Model	Coefficient of MA component	AIC	BIC
SARIMA $(0,1,0)(0,1,0)_{12}$	-	6983.58	6987.98
SARIMA $(0,1,0)(0,0,0)_{12}$	-	6693.07	6697.5
SARIMA $(0,2,1)(0,0,0)_{12}$	-	6664.44	6673.28
SARIMA $(0,2,2)(0,0,0)_{12}$	-1.9970 0.9992	6634.21	6647.47

Figure 7 shows the diagnostic plots for residuals from the ARIMA (0,1,0) model.

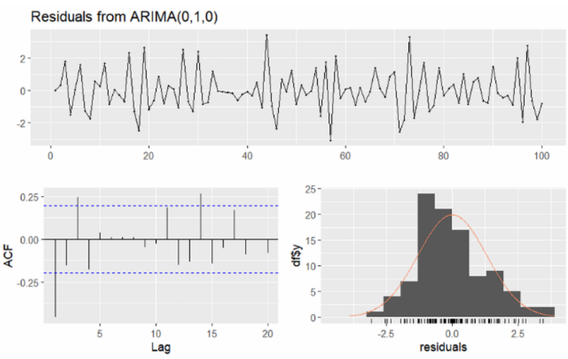

Figure 7 Diagnostic plots for residuals from ARIMA (0,1,0) model

Based on Figure 7, the model appears to be stationary and approximately normally distributed, as almost all residuals' data fall within the normality range. The top panel illustrates the residuals fluctuating around zero, indicating the absence of any noticeable patterns. The ACF plot is displayed in the bottom left panel, showing most autocorrelations within the 95% confidence interval, indicating no significant autocorrelation. The bottom right panel features a histogram with a normal distribution curve, showing that the residuals are approximately normally distributed. These plots suggest that the ARIMA (0,1,0) model fits the data well. The visualization in Figure 8 confirmed the normality in the residuals from ARIMA (0,1,0) model.

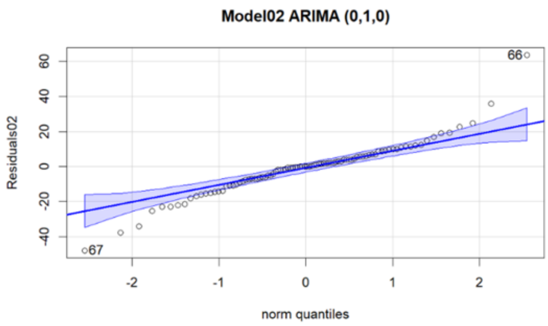

Figure 8 Q-Q Plot of residuals for ARIMA (0,1,0)

Based on Figure 8, the close alignment of points to the diagonal line suggests that the residuals are approximately normally distributed, with some deviation at the extremes, indicating a reasonably good fit for the ARIMA model.

In stationary form, the forecast series is then compared with the series out-of-sample to determine the forecast error [13]. The validity and accuracy of a forecasting model are assessed using the cross-validation (CV) method. The model chosen is evaluated based on three evaluation criteria: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). This analysis uses the data from May 2011 until March 2024 for testing. Figure 9 displays the historical and forecasted prices of coconut oil from May 2011 to March 2024. The blue line represents the actual observed prices, showing fluctuations over time with notable peaks and troughs. The red dashed line indicates the forecasted prices based on a model, which remains relatively stable compared to the historical data. Surrounding the forecast, the green dashed lines represent the 95% prediction

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interval, illustrating the range within which the future prices are expected to fall with 95% confidence. This interval widens as the forecast horizon extends, reflecting increased uncertainty in the predictions. While the forecast suggests stable future prices, the broadening prediction interval highlights the potential variability and uncertainty in the coconut oil market. Table 5 compares forecast and actual values from June 2023 to March 2024. The actual value column shows the real data for each month, which fluctuates between 1012.73 in June 2023 and 1287.86 in March 2024. In contrast, the Forecast Value remains constant at 1287.86 throughout the entire period, indicating that the forecast model predicted a steady value without accounting for the observed variations. The Low 95% and Upper 95% bounds show the range within which the actual values are expected to fall. The best model, ARIMA (0,1,0), is evaluated based on mean average percentage error (MAPE) and prediction intervals (PI). The forecast errors, RMSE, MAE, and MAPE, are presented in Table 6. A MAPE of 27% suggests that while the forecasting model's accuracy is reasonable, refinement can further reduce the prediction errors [14].

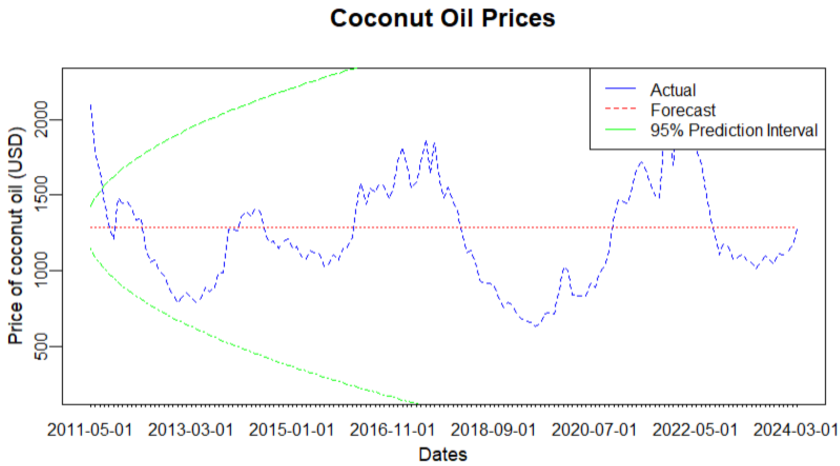

Figure 9 Historical and forecasted prices of coconut oil from May 2011 to March 2024

Table 5 Comparison of forecast value and actual value from June 2023 to March 2024

Observation	Actual Value	Forecast Value	Low 95%	Upper 95%
June 2023	1012.73	1287.86	1212.86	1374.25
July 2023	1047.38	1287.86	1150.76	1424.96
August 2023	1099.09	1287.86	1093.97	1481.75
September 2023	1071.67	1287.86	1050.39	1525.33
October 2023	1046.43	1287.86	1013.65	1562.07
November 2023	1114.55	1287.86	981.29	1594.43
December 2023	1108.81	1287.86	952.03	1623.69
January 2024	1130.57	1287.86	925.12	1650.60
February 2024	1171.58	1287.86	900.07	1675.648
March 2024	1287.86	1287.86	876.55	1699.17

Table 6 Forecasting performance

Forecast performance	ARIMA (0,1,0)
RMSE	3.529529
MAE	2.968829
MAPE	27.05739

Figure 10 illustrates a forecast plot of coconut oil prices with 95% prediction intervals from April 2024 to December 2024. The plot displays the forecasted price as a central line with upper and lower bounds representing the prediction interval, indicating the range within which the actual prices are expected to fall with 95% confidence.

Table 7 complements this visualization by providing the specific forecast values and their corresponding 95% prediction intervals for each month within the forecast period. The forecasted price of coconut oil remains constant at 1287.86 USD/mt. At the same time, the lower and upper bounds of the prediction

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intervals gradually widen, reflecting increasing uncertainty over time, with the lower bound starting at 1150.7564 USD/mt in April 2024 and decreasing to 876.5491 USD/mt in December 2024 and the upper bound starting at 1424.964 USD/mt in April 2024 and increasing to 1699.171 USD/mt in December 2024. The ARIMA (0,1,0) or known as random walk model with $p = 0, d = 1, q = 0$ can be written as Equation 3:

$$y_t = y_{t-1} + a_t \text{ .... } \textbf{Equation 3}$$

where y_t is the price of coconut oil at time t, y_{t-1} is the value of the price of coconut oil in the previous time period, $t - 1$ and a_t is the error term.

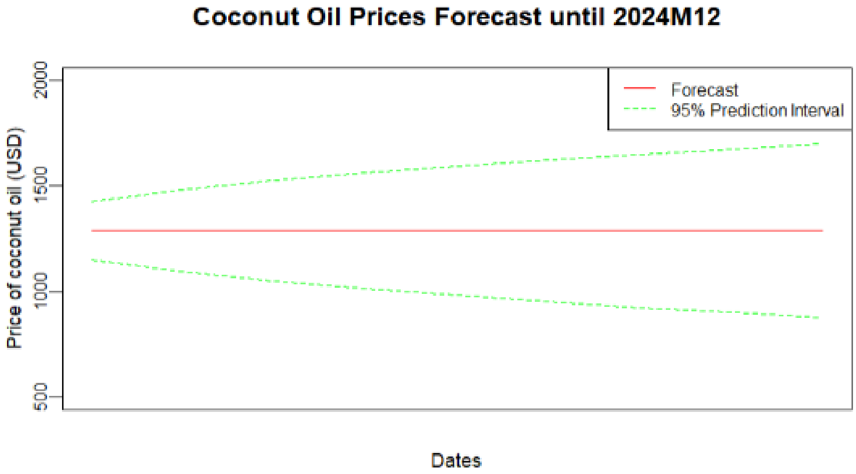

Figure 10 Forecasting plot from April 2024 to December 2024

Table 7 Forecasting coconut oil prices from April 2024 to December 2024

Month	Forecast	Low 95%	Upper 95%
April 2024	1287.86	1150.7564	1424.964
May 2024	1287.86	1093.9662	1481.754
June 2024	1287.86	1050.3896	1525.330
July 2024	1287.86	1013.6528	1562.067
August 2024	1287.86	981.2870	1594.433
September 2024	1287.86	952.0261	1623.694
October 2024	1287.86	925.1179	1650.602
November 2024	1287.86	900.0724	1675.648
December 2024	1287.86	876.5491	1699.171

V. CONCLUSION

This research used the Box-Jenkins methodology to model and forecast coconut oil prices using time series data. The study systematically applied the steps of model identification, estimation, diagnostic checking, and forecasting to develop an appropriate ARIMA model that best captures the underlying patterns in the coconut oil price data. The ARIMA (0,1,0) model has been identified as the most appropriate model for forecasting coconut oil prices from April 2024 to December 2024 with low AIC (6693.07) and BIC (6697.5) values. This model was selected based on its ability to accurately capture the underlying trend in the price data without overfitting. The forecasted values and their 95% prediction intervals demonstrate the model's efficacy, which provides reliable and stable predictions. The forecast remains constant at 1287.86 USD/mt throughout the forecast period. The prediction intervals gradually widen to accommodate increasing uncertainty over time. This model's simplicity and robustness make it a practical choice for stakeholders who depend on coconut oil price forecasts for planning and decision-making. The government and other economic institutions can also apply the forecasting to take necessary actions to benefit coconut oil end users.

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