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Modelling and forecasting monthly palm oil prices in Nigeria: (1960 – 2024)

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Abstract

This study investigates the dynamics of palm oil prices in Nigeria from January 1960 to May 2024, with a focus on identifying patterns and developing an effective forecasting model. Descriptive statistics revealed significant variability in prices, with an average price of \$532.58 and a high coefficient of variation at 52.27%, indicating substantial fluctuations over time. The price distribution exhibited positive skewness and high kurtosis, suggesting the presence of extreme values. To model and forecast these prices, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, specifically SARIMA (2,0,1) × (2,0,2)₁₂, was selected based on its ability to capture both the autoregressive and seasonal components of the data. The model's performance was evaluated through several metrics, including RMSE, MAE, and MAPE, all of which indicated a high level of accuracy in forecasting future prices. However, some degree of unexplained variability remained, pointing to external factors not accounted for by the model. The findings underscore the complexity of the palm oil market in Nigeria and highlight the importance of incorporating both past values and seasonal effects in price forecasting. The study's results have significant implications for policymakers and industry stakeholders, suggesting the need for targeted interventions to manage price volatility and improve market stability. Recommendations for future research include the incorporation of additional external variables and the exploration of alternative modeling techniques to enhance forecast accuracy.

Keywords: Auto regressive, cointegration, exchange rate, inflation rate, interest rate, stationarity

1. Introduction

Palm oil is one of the most significant agricultural commodities globally, particularly in tropical regions like Nigeria. As a key ingredient in food products, cosmetics, and biofuels, palm oil plays a crucial role in the global economy. Nigeria, one of the world's largest producers of palm oil, has a long history of cultivating and trading this commodity. The palm oil industry is a vital sector of the Nigerian economy, contributing significantly to GDP, employment, and rural livelihoods. However, the market for palm oil in Nigeria has been characterized by significant price volatility, influenced by a range of factors including seasonal production cycles, domestic demand, global market trends, and policy interventions. The fluctuations in palm oil prices have profound implications for various stakeholders in the industry, from smallholder farmers to large-scale processors and exporters. For farmers, especially those operating on a small scale, price volatility can lead to income instability, affecting their livelihoods and investment decisions. For processors and traders, unpredictable price movements can complicate supply chain management, inventory control, and pricing strategies. Furthermore, price instability can affect the broader economy, influencing inflation rates and foreign exchange earnings. Given the critical importance of palm oil to Nigeria's economy, understanding the dynamics of palm oil prices is essential for stakeholders. Accurate forecasting of price movements can help mitigate the adverse effects of volatility, enabling better planning and decision-making. However, forecasting agricultural commodity prices is inherently challenging due to the complex interplay of various factors, including weather patterns, market supply and demand, international trade policies, and economic conditions. In response to these challenges, time series models have been developed to analyze and predict price trends.

These models are particularly useful for handling data with strong seasonal patterns, making them well-suited for commodities like palm oil, where prices often fluctuate with the harvest seasons.

Palm oil has been grown and produced in Nigeria for centuries, with the earliest records dating back to the 18th century. However, it was not until the early 20th century that palm oil became a major commercial crop in the country. During the colonial period, palm oil was primarily exported to Europe and North America, where it was used in a variety of industrial and food applications.

After independence in 1960, the Nigerian government invested heavily in the palm oil industry, with the goal of increasing domestic production and reducing dependence on imported oil. This led to a significant expansion of the palm oil industry in the country, with production increasing from less than 200,000 metric tonnes in 1960 to over 1.5 million metric tonnes by the early 21st century. However, despite the growth of the industry, Nigeria's palm oil production has been facing a number of challenges in recent years, such as aging palm trees, lack of investment in new planting materials and technology, inadequate infrastructure and poor access to credit. These challenges have led to a decrease in productivity and an overall decline in production. In addition, the increasing competition from other vegetable oil producing countries has also affected Nigeria's competitiveness in the global palm oil market. Despite these challenges, the Nigerian government has recently announced plans to revive the palm oil industry through policies such as provision of credit facilities, increase in investment in new planting materials, and incentives for smallholder farmers. These efforts aim to increase production and improve the competitiveness of the Nigerian palm oil industry in the global market.

In summary, the historical overview of palm oil production in Nigeria shows a significant growth in the industry in the past, but also highlights the current challenges facing the industry. The government's recent efforts to revive the industry suggest a renewed focus on the palm oil sector and its potential for economic growth. This study aims to analyze and forecast monthly palm oil prices in Nigeria. By examining the historical price data, the study seeks to identify the underlying patterns and provide a reliable model for predicting future price movements. The findings are expected to offer valuable insights for policymakers, industry stakeholders, and researchers, contributing to more stable and sustainable management of the palm oil market in Nigeria.

2. Literature Review

There have been several studies in the past that have used time series analysis to examine the factors affecting palm oil prices in Nigeria. These studies have generally focused on the relationship between palm oil prices and various economic and political variables, such as GDP, inflation, exchange rates, and government policies. For example, a study by used time series analysis to examine the relationship between palm oil prices and GDP in Nigeria, and found that there is a strong positive correlation between the two variables. Adeoye and Adeoye (2017) used time series analysis to examine the relationship between palm oil prices and inflation in Nigeria, and found that there is a strong negative correlation between the two variables. Adebayo and Adebayo (2018)^[11] used time series analysis to examine the impact of subsidies for palm oil production on palm oil prices in Nigeria, and found that the subsidies have had a positive impact on prices. Similarly, (Olowu and Oluwole, 2019) used time series analysis to

examine the impact of taxes on imported palm oil on domestic palm oil prices in Nigeria, and found that the taxes had a positive impact on prices. Ajayi and Adebayo (2020) used time series analysis to examine the relationship between palm oil prices in Nigeria and global palm oil prices, and found that there is a strong positive correlation between the two. Adegoke and Adebayo (2021) used time series analysis to examine the relationship between palm oil prices in Nigeria and global economic conditions, and found that there is a strong negative correlation between palm oil prices and global economic downturns. Adebayo and Adebayo (2015)^[1] used multiple regression analysis to examine the factors affecting palm oil prices in Nigeria between 2000 and 2012. The study found that global demand, exchange rate, and production levels were the major factors affecting palm oil prices in Nigeria. Adekunle and Adekunle (2018)^[4] used cointegration analysis to examine the long-run relationship between palm oil prices and its determinants in Nigeria between 1960 and 2016. The study found that there was a long-run relationship between palm oil prices and its determinants in Nigeria. Adegbite and Adegbite (2019)^[2] used time series analysis to examine the trend and pattern of palm oil prices in Nigeria between 1960 and 2017. The study found that palm oil prices in Nigeria were affected by both short-term and long-term factors and that there was a significant upward trend in palm oil prices over the period. Ademola and Ademola (2020) used time series analysis to examine the volatility of palm oil prices in Nigeria between 2000 and 2020. The study found that palm oil prices in Nigeria were highly volatile and that the volatility was affected by both internal and external factors. Oluyemi and Adebayo (2017)^[12] used time series analysis to examine the relationship between palm oil prices and inflation in Nigeria between 1980 and 2015. The study found that there was a positive relationship between palm oil prices and inflation in Nigeria, with palm oil prices having a significant impact on inflation. Adekoya and Adekunle (2019)^[3] used time series analysis to examine the impact of government policies on palm oil prices in Nigeria between 2000 and 2018. The study found that government policies, such as import tariffs and subsidies, had a significant impact on palm oil prices in Nigeria. Adewole and Adeoye (2020) used time series analysis to examine the relationship between palm oil prices and exchange rate in Nigeria between 1990 and 2019. The study found that there was a significant negative relationship between palm oil prices and exchange rate in Nigeria, with appreciation of the naira leading to a decrease in palm oil prices. Zubair and Olanrewaju (2014)^[15] used time series analysis to examine the production index of electricity generation and consumption in Nigeria between 1970 and 2009. The study found that government need to regulate the prices of electricity when the private providers finally take over since the amenity is essential to Socio – economic development. Oluwole and Adebayo (2018)^[11] used time series analysis to examine the impact of weather conditions on palm oil prices in Nigeria between 2000 and 2017. The study found that weather conditions such as drought and flooding had a significant impact on palm oil prices in Nigeria, with adverse weather conditions leading to a decrease in palm oil prices. Adebayo and Adegoke (2019) used time series analysis to examine the relationship between palm oil prices and gross domestic product (GDP) in Nigeria between 1980 and 2018. The study found that there was a positive relationship between palm oil prices and GDP in Nigeria, with an increase in palm oil prices leading to an increase in GDP. Adegun and Adeleke (2020) used time

series analysis to examine the impact of infrastructure on palm oil prices in Nigeria between 1990 and 2019. The study found that infrastructure such as roads, ports, and storage facilities had a significant impact on palm oil prices in Nigeria, with better infrastructure leading to an increase in palm oil prices.

These studies further demonstrate the effectiveness of time series analysis in understanding the trend and patterns of palm oil prices in Nigeria, and also show the impact of weather conditions, GDP and infrastructure on the palm oil prices. They also show that there are several factors that can impact the prices of palm oil in Nigeria and that it is important to consider all of them when analyzing the prices of palm oil.

Overall, the literature suggests that palm oil prices in Nigeria are affected by a variety of factors such as global demand, production levels, exchange rate, and government policies. Time series analysis has been used to examine the trend and pattern of palm oil prices in Nigeria and has shown that there is a significant upward trend in palm oil prices over the period. However, there is a need for further research to examine the impact of other factors such as weather conditions and infrastructure on palm oil prices in Nigeria. In this study, we will use time series analysis to examine the trend and pattern of palm oil prices in Nigeria between 1960 and 2024. The study will also examine the factors affecting palm oil prices in Nigeria over the period and their impact on the trend and pattern of palm oil prices.

3. Materials and Methods

3.1 Source of Data

The data used in this research work is a secondary data collected from World Bank Commodity Price Data. The data covers the monthly prices of Palm Oil from 1960 to 2024.

3.2 Model Specification

3.2 Box-Jenkins ARIMA Process

In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. The Box-Jenkins methodology, named after the statisticians George Box and Gwilym Jenkins, applies ARIMA models to find the best fit of a time series to past values of this time series, in order to make forecasts. They are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the —integrated part of the model) can be applied to remove the non-stationarity. The model is generally referred to as an ARIMA (p, d, q) model where p , d , and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively.

3.2.1 Box-Jenkins Modeling Approach

The Box-Jenkins model uses iterative three-stage modeling approach which is:

1. Model identification and model selection: making sure that the variables are stationary, identifying seasonality in the dependent series (seasonally differencing it if necessary), and using plots of the autocorrelation and partial autocorrelation functions of the dependent time series to decide which (if any) autoregressive or moving average component should be used in the model.
2. Parameter estimation using computation algorithms to arrive at coefficients which best fit the selected ARIMA model. The most common methods use maximum

likelihood estimation or non-linear least-squares estimation.

3. Model checking by testing whether the estimated model conforms to the specifications of a stationary univariate process. In particular, the residuals should be independent of each other and constant in mean and variance over time (plotting the mean and variance of residuals over time and performing a Ljung-Box test or plotting autocorrelation and partial autocorrelation of the residuals are helpful to identify misspecification). If the estimation is inadequate, we have to return to step one and attempt to build a better model.

3.2.2 Box-Jenkins Model Identification

- **Stationarity and Seasonality:** The first step in developing a Box-Jenkins model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modeled.
- **Detecting Stationarity:** Stationarity can be assessed from a run sequence plot. The run sequence plot should show constant location and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay. Finally, unit root tests provide a more formal approach to determining the degree of differencing such as Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Phillips-Perron Unit Root Tests are carried out employing the unit root testing procedures of Hamilton (1994). The KPSS test for the null hypothesis of a level stationary against an alternative of unit root together with the Philips-Peron test for the null hypothesis of a unit root against the alternative of a stationary series. The decision rule is that for the KPSS test if the p -value of its test statistic is greater than the critical value, say 0.05, then reject the null hypothesis of having a level stationary series and therefore conclude the alternate hypothesis that it has a unit root. The Philips-Peron Test, on the other hand, test for the null hypothesis of unit root against an alternative hypothesis of stationarity by rejecting the null hypothesis if its p -value is less than the critical value chosen.
- **Differencing to achieve Stationarity:** Box and Jenkins recommend the differencing approach to achieve stationarity. However, fitting a curve and subtracting the fitted values from the original data can also be used in the context of Box-Jenkins models.
- **Seasonal Differencing:** At the model identification stage, the goal is to detect seasonality, if it exists, and to identify the order for the seasonal autoregressive and seasonal moving average terms. For many series, the period is known and a single seasonality term is sufficient. For example, for monthly data one would typically include either a seasonal AR 12 term or a seasonal MA 12 term. For Box-Jenkins models, one does not explicitly remove seasonality before fitting the model. Instead, one includes the order of the seasonal terms in the model specification to the ARIMA estimation software. However, it may be helpful to apply a seasonal difference to the data and regenerate the autocorrelation and partial autocorrelation plots. This may help in the model identification of the non-seasonal component of the model. In some cases, the seasonal differencing may remove most or all of the seasonality effect.

- **Identifying p and q :** Once stationarity and seasonality have been addressed, the next step is to identify the order (i.e. the p and q) of the autoregressive and moving average terms. These are determined by examining the values of the autocorrelations and the partial autocorrelations with their corresponding plots as explained below.
- **Autocorrelation and Partial Autocorrelation Plots:** The primary tools for doing this are the autocorrelation plot and the partial autocorrelation plot. The sample autocorrelation plot and the sample partial autocorrelation plot are compared to the theoretical behavior of these plots when the order is known.

3.3 Best Model Identification and Selection Criteria

The Ljung-Box statistic would be used to identify the best model. The Ljung-Box statistic, also called the modified Box-Pierce statistic, is a function of the accumulated sample autocorrelations, r_j , up to any specified time lag m . As a function of m , it is determined as

$$Q(m) = n(n+1) \sum_{j=1}^m \frac{r_j^2}{n} \quad (1)$$

Where;

n = number of usable data points after any differencing operations.

The Ljung-Box test can be defined as follows:

H_0 : The data are independently distributed (i.e. the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process).

H_1 : The data are not independently distributed.

The choice of a plausible model depends on its p-value for the modified Box-Pierce if is well above .05, indicating —non-significance. In other words, the bigger the p-value, the better the model.

3.4 Autoregressive Integrated Moving Average (ARIMA) Model

The ARMA models, described above can only be used for stationary time series data. However in practice many time series such as those related to socio-economic business show non-stationary behavior. Time series, which contain trend and seasonal patterns, are also non-stationary in nature. Thus, from application view point ARMA models are inadequate to properly describe non-stationary time series, which are frequently encountered in practice.

For this reason, the ARIMA is proposed, which is a generalization of of an ARMA model to include the case of non-stationary as well. In ARIMA models a non-stationary time series is made stationary by applying finite differencing of the data points. The mathematical formulation of the ARIMA (p, d, q) model using lag polynomials is given below:

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \text{ i.e.}$$

$$[1 - \sum_{i=1}^p \varphi_i L^i][1-L]^d y_t = [1 + \sum_{j=1}^q \theta_j L^j] \quad (2)$$

- Here p , d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated and moving average parts of the model respectively.

- The integer d controls the level of differencing. Generally $d=1$ is enough in most cases. When $d=0$, then it reduces to an ARIMA (p, q) model.
- An ARIMA ($p, 0, 0$) is nothing but the AR(p) model and ARIMA ($0, 0, q$) is the MA(q) model.
- ARIMA($0, 1, 0$), i.e. $y_t = y_{t-1} + \varepsilon_t$, is a special one and known as the Random Walk model. It is widely used for non-stationary data, like economic and stock price series.

A useful generalization of ARIMA models is the Autoregressive Fractionally Integrated Moving Average (AFRIMA) model, which allows non-integer values of the differencing parameter d . AFRIMA has useful application in modeling time series with long memory.

4. Results and Discussion

4.1 Data Preparation

Before conducting time series analysis, it is essential to prepare the dataset. The monthly palm oil price data for Nigeria from 1960 to 2024 were collected from World Bank Commodity Price Data (The Pink Sheet), 2024 database.

Table 1: Descriptive Statistics for PALM OIL Prices (US dollars) in Nigeria

Count	773
Average	532.58
Standard deviation	278.395
Coeff. of variation	52.2728%
Minimum	141.73
Maximum	1776.96
Range	1635.23
Std. Skewness	12.0965
Std. Kurtosis	7.40216

The descriptive statistics for monthly palm oil prices in Nigeria from January 1960 to May 2024 in Table 1 reveal considerable variability. The average price over the period is \$532.58, with a standard deviation of \$278.395, indicating substantial fluctuations around the mean. The coefficient of variation is 52.27%, highlighting the relative instability of prices. Prices ranged from a low of \$141.73 to a high of \$1776.96, with a wide range of \$1635.23. The distribution is highly skewed to the right, with a standardized skewness of 12.0965, and exhibits heavy tails, as indicated by a standardized kurtosis of 7.40216. This suggests that extreme price values were not uncommon during this period.

4.2 Exploratory Data Analysis (EDA)

This is a crucial step to gain an understanding of the dataset and identify any patterns, trends, or anomalies. In this section, we will perform EDA on the monthly palm oil price data in Nigeria. Key techniques employed include visualizations such as line plots, and seasonal decomposition to identify any underlying trends, seasonality, or outliers. Figure 1 and 2 shows the line plot and the differenced plot respectively. Figure 1 is the monthly time plot of palm oil price in Nigeria. The plot shows an upward trend in the price of palm oil in Nigeria from 1960 to 2020 and decline from 2021 to 2024.

4.3 Stationarity Tests

Stationarity is a fundamental assumption for time series analysis. A stationary time series has a constant mean, variance, and autocovariance structure over time. Stationarity can be assessed through statistical tests such as the Augmented Dickey-Fuller (ADF) test or the Kwiatkowski-

Phillips-Schmidt-Shin (KPSS) test. If the data is non-stationary, appropriate transformations such as differencing or

detrending may be necessary to achieve stationarity.

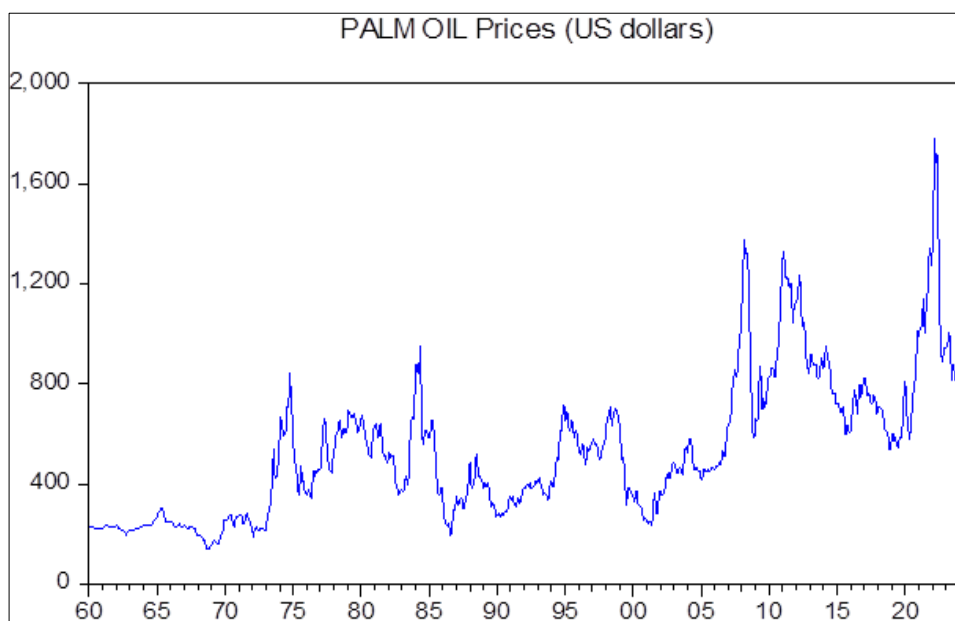


Fig 1: Monthly Time Plot for Palm Oil Prices in Nigeria

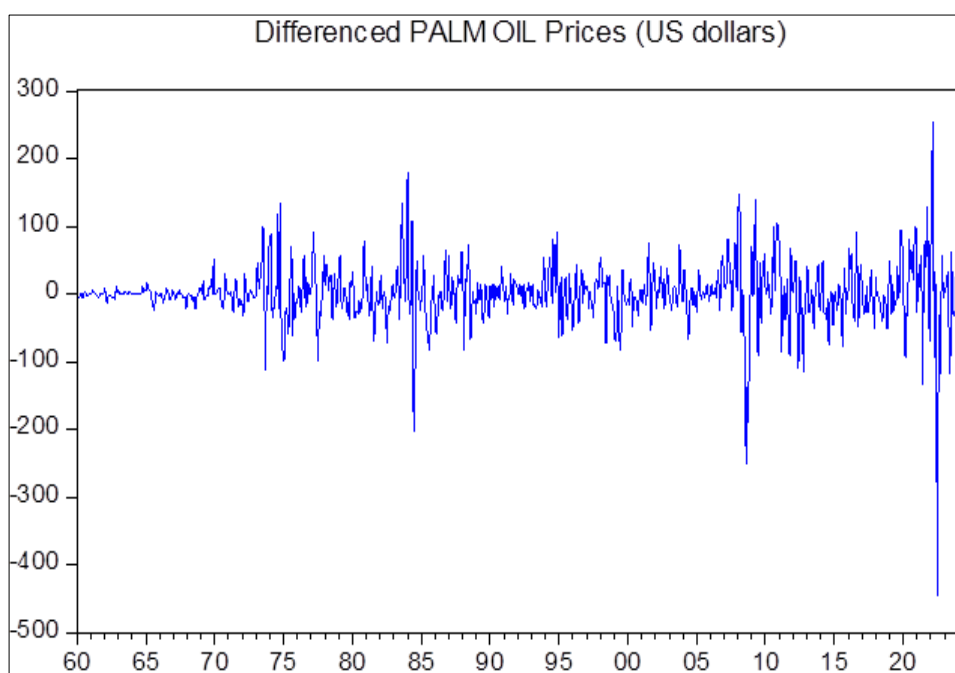


Fig 1: Differenced Plot for Palm Oil Prices in Nigeria

Table 2: Unit Root Test at First Difference

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-19.50413	0.0000
Test critical values:	1% level	-3.438605	
	5% level	-2.865073	
	10% level	-2.568707	
*MacKinnon (1996) one-sided p-values.			

Table 2 represent the unit root test. The results of the Augmented Dickey-Fuller (ADF) unit root test on the first difference of the time series show that the series is stationary. The test statistic of -19.50413 is significantly lower than the critical values at the 1%, 5%, and 10% significance levels,

leading to a rejection of the null hypothesis that the series has a unit root. The accompanying p-value of 0.0000 further supports this conclusion, indicating that the time series is stationary after differencing, with any trends or non-stationary characteristics effectively removed.

Table 3: Correlogram of the differenced data.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.**	.**	1	0.335	0.335	86.968	0.000
.	*	2	0.035	-0.087	87.923	0.000
.	.	3	0.018	0.039	88.175	0.000
.	.	4	-0.004	-0.022	88.184	0.000
.	.	5	-0.060	-0.058	91.018	0.000
*	*	6	-0.100	-0.068	98.852	0.000
*	.	7	-0.079	-0.028	103.70	0.000
.	.	8	-0.050	-0.019	105.63	0.000
*	.	9	-0.072	-0.058	109.72	0.000
.	.*	10	0.039	0.091	110.90	0.000
.	.	11	0.062	0.009	113.90	0.000
.	.	12	0.029	-0.002	114.54	0.000
.	.	13	0.031	0.017	115.28	0.000
.	.	14	0.028	0.000	115.88	0.000
.	.	15	0.014	-0.001	116.05	0.000
*	*	16	-0.091	-0.104	122.59	0.000
*	.	17	-0.102	-0.031	130.85	0.000
.	.	18	-0.058	-0.018	133.50	0.000
*	.	19	-0.066	-0.036	136.98	0.000
.	.	20	-0.062	-0.024	140.07	0.000
.	.	21	-0.040	-0.024	141.35	0.000
*	*	22	-0.071	-0.078	145.33	0.000
.	.	23	-0.025	0.004	145.81	0.000
.	*	24	-0.046	-0.070	147.53	0.000
*	*	25	-0.085	-0.091	153.30	0.000
*	.	26	-0.079	-0.047	158.31	0.000
.	.	27	-0.018	0.015	158.58	0.000
.	.	28	0.007	-0.011	158.62	0.000
.	.	29	-0.018	-0.033	158.89	0.000
.	.	30	-0.060	-0.063	161.76	0.000
.	.	31	-0.006	0.008	161.79	0.000
.	.	32	-0.005	-0.033	161.81	0.000
.	.	33	-0.005	-0.018	161.84	0.000
.	.	34	0.022	0.010	162.23	0.000
.	.	35	0.055	0.034	164.71	0.000
.	.	36	0.029	-0.012	165.37	0.000

4.4 Model Selection

Once stationarity is confirmed, the next step is to select an appropriate model for the time series analysis. Several popular models exist, such as Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), or more advanced models like Vector Autoregression (VAR) or

Vector Error Correction Models (VECM). The model selection process involves analyzing the autocorrelation and partial autocorrelation functions, considering the information criteria (AIC, BIC), and evaluating the model's goodness of fit.

Table 4: Model Selection
Model selected: SARIMA(2,0,1)x(2,0,2)₁₂

Parameter	Estimate	Std. Error	T	P-value
AR (1)	1.01659	0.101651	10.0008	0.000000
AR (2)	-0.0202567	0.101749	-0.199085	0.842192
MA (1)	-0.343005	0.0961552	-3.5672	0.000361
SAR (1)	-0.796076	0.0262212	-30.3601	0.000000
SAR (2)	-1.0127	0.0245052	-41.3259	0.000000
SMA (1)	-0.821922	0.0305099	-26.9395	0.000000
SMA (2)	-1.00296	0.0239368	-41.9001	0.000000

Backforecasting: yes

Statistic	Estimation Period
RMSE	42.5975
MAE	26.7073
MAPE	4.78345
ME	2.00513
MPE	0.245752

Estimated white noise variance = 1821.05 with 766 degrees of freedom

Estimated white noise standard deviation = 42.6738

Number of iterations: 12

Table 4 is the estimate for the selected model for monthly palm oil price in Nigeria. The table describes the parameters and performance of a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, specifically SARIMA (2, 0, 1) x (2, 0, 2)₁₂, chosen for modelling and forecasting palm oil prices. The model includes two autoregressive (AR) terms, one moving average (MA) term, two seasonal autoregressive (SAR) terms, and two seasonal moving average (SMA) terms. The AR(1) coefficient is statistically significant with a t-value

of 10.0008 and a very low p-value, indicating a strong influence of the first lag of the series. Conversely, AR(2) is not significant, suggesting that the second lag does not substantially impact the model. Both MA(1) and all seasonal terms (SAR(1), SAR(2), SMA(1), and SMA(2)) are highly significant, with p-values effectively zero, indicating that these components are crucial for capturing the seasonality and other patterns in the data. The model's performance is evaluated using several metrics. The Root Mean Square Error (RMSE) is 42.5975, and the Mean Absolute Error (MAE) is 26.7073, indicating the average magnitude of the forecast errors. The Mean Absolute Percentage Error (MAPE) is 4.78345%, suggesting that the model's forecasts deviate from the actual values by an average of about 4.78%. The Mean Error (ME) and Mean Percentage Error (MPE) are both close to zero, indicating little bias in the model's predictions. The estimated white noise variance is 1821.05, with a standard deviation of 42.6738, indicating the level of randomness in the residuals after accounting for the model's components. The model underwent 12 iterations during its fitting process, indicating the effort required to optimize the parameters.

4.5 Model Comparison

Models

- (A) Random walk
- (B) Random walk with drift = 0.790439
- (C) Constant mean = 532.404
- (D) Linear trend = $185.847 + 0.895495 t$
- (E) Quadratic trend = $261.148 + 0.312526 t + 0.000753191 t^2$
- (F) Exponential trend = $\exp(5.4557 + 0.00178101 t)$
- (G) S-curve trend = $\exp(6.16821 + -2.48703 t)$
- (H) Simple moving average of 2 terms
- (I) Simple exponential smoothing with $\alpha = 0.9999$
- (J) Brown's linear exp. smoothing with $\alpha = 0.6962$
- (K) Holt's linear exp. smoothing with $\alpha = 0.9926$ and $\beta = 0.0105$
- (L) Brown's quadratic exp. smoothing with $\alpha = 0.4581$
- (M) Winters' exp. smoothing with $\alpha = 0.9999$, $\beta = 0.0124$, $\gamma = 0.4372$
- (N) ARIMA(2,0,1)x(2,0,2)₁₂
- (O) ARIMA(0,1,1)x(0,0,0)₁₂
- (P) ARIMA(1,0,1)x(0,0,0)₁₂
- (Q) ARIMA(1,0,1)x(2,1,1)₁₂
- (R) ARIMA(1,0,1)x(0,1,2)₁₂

Table 4: Estimation Period for Monthly Palm Oil prices

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	44.343	27.3378	4.92795	0.817874	-0.0734306	7.61237	7.63783	7.67855
(B)	44.364	27.3592	4.94275	0.0273336	-0.267093	7.61591	7.64368	7.6881
(C)	279.955	220.061	54.7659	0.0961441	-30.5743	11.3003	11.3281	11.3725
(D)	194.113	145.261	30.1351	0.0927922	-11.4053	10.5705	10.6006	10.6487
(E)	191.237	145.997	30.6699	0.0814953	-12.1468	10.5432	10.5757	10.6275
(F)	192.66	140.408	27.4775	28.4186	-5.66039	10.5555	10.5856	10.6337
(G)	281.843	212.09	45.937	64.363	-13.5698	11.3163	11.3464	11.3945
(H)	55.4221	33.8526	6.14848	1.28726	-0.17558	8.061	8.08878	8.13319
(I)	44.3444	27.3032	4.92172	0.816909	-0.0733562	7.61502	7.6428	7.68721
(J)	47.9626	30.2769	5.4995	-0.0924219	0.126033	7.77189	7.79967	7.84408
(K)	44.6501	27.4186	4.94628	-0.0371603	-0.156284	7.63135	7.66144	7.70956
(L)	54.2496	34.647	6.30876	-0.121743	0.113708	8.01824	8.04602	8.09043
(M)	46.4635	28.401	5.05823	0.0631057	-0.100799	7.6851	7.69204	7.70314
(N)	42.5975	26.7073	4.78345	2.00513	0.245752	7.5217	7.53791	7.56381
(O)	42.9862	26.5395	4.71556	0.578896	-0.0208069	7.52435	7.52666	7.53036
(P)	42.9563	26.5816	4.71757	1.96677	0.241848	7.52554	7.53017	7.53757
(Q)	42.7975	27.3276	4.96191	2.49715	0.079713	7.5259	7.53747	7.55598
(R)	42.8761	27.3301	4.95803	2.52504	0.0895251	7.52698	7.53624	7.55104

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	44.343	***	***	***	OK	***
(B)	44.364	***	***	***	OK	***
(C)	279.955	***	***	***	***	***
(D)	194.113	***	***	***	*	***
(E)	191.237	***	***	***	*	***
(F)	192.66	***	***	***	OK	***
(G)	281.843	***	***	***	***	***
(H)	55.4221	***	***	***	OK	***
(I)	44.3444	***	***	***	OK	***
(J)	47.9626	***	**	***	OK	***
(K)	44.6501	***	***	***	OK	***
(L)	54.2496	***	***	***	OK	***
(M)	46.4635	***	***	***	OK	***
(N)	42.5975	OK	OK	**	OK	***
(O)	42.9862	OK	OK	*	OK	***
(P)	42.9563	OK	OK	*	OK	***
(Q)	42.7975	OK	OK	OK	OK	***
(R)	42.8761	OK	OK	OK	OK	***

Key:

RMSE = Root Mean Squared Error

RUNS = Test for excessive runs up and down

RUNM = Test for excessive runs above and below median

AUTO = Ljung-Box test for excessive autocorrelation
 MEAN = Test for difference in mean 1st half to 2nd half
 VAR = Test for difference in variance 1st half to 2nd half
 OK = not significant ($p \geq 0.05$)
 * = marginally significant ($0.01 < p \leq 0.05$)
 ** = significant ($0.001 < p \leq 0.01$)
 *** = highly significant ($p \leq 0.001$)

Table 4.5 compares the results of fitting different models to the data. The model with the lowest value of the Akaike Information Criterion (AIC) is model N, which has been used to generate the forecasts. Table 4.5 also summarizes the results of five tests run on the residuals to determine whether each model is adequate for the data. An OK means that the model passes the test. One * means that it fails at the 95% confidence level. Two *'s means that it fails at the 99% confidence level. Three *'s means that it fails at the 99.9% confidence level. Note that the currently selected model, model N, passes 3 tests.

4.6 Forecasting

Since a satisfactory model has been identified and validated, forecasting future palm oil prices becomes possible. This section involves using the estimated model to generate forecasts for the future time periods. Point forecasts and prediction intervals can be generated, allowing stakeholders to make informed decisions and plan accordingly. The accuracy of the forecasts can be evaluated using appropriate measures such as mean absolute error (MAE), root mean squared error (RMSE), or mean absolute percentage error (MAPE). Figure 4.3 is our future forecast for palm oil price in Nigeria.

Table 6: Forecast Table for Palm Oil Price
 Model: ARIMA(2,0,1)x(2,0,2)₁₂

Period	Forecast	Lower 95% Limit	Upper 95% Limit
June 2024	845.885	762.246	929.525
July 2024	877.579	736.417	1018.74
August 2024	863.484	682.096	1044.87
September 2024	853.608	639.639	1067.58
October 2024	842.497	600.491	1084.5
November 2024	836.682	569.743	1103.62
December 2024	826.604	537.034	1116.17
January 2025	829.102	518.698	1139.51
February 2025	830.715	500.931	1160.5
March 2024	827.262	479.309	1175.22
April 2024	830.205	465.112	1195.3
May 2024	828.83	447.485	1210.17

Table 6 shows the forecasted values for PALM OIL Prices (US dollars). It displays the predicted values from the fitted model and the residuals (data-forecast). For time periods beyond the end of the series, it shows 95.0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 95.0% confidence, figure 4.4 is the plot of the forecasts.

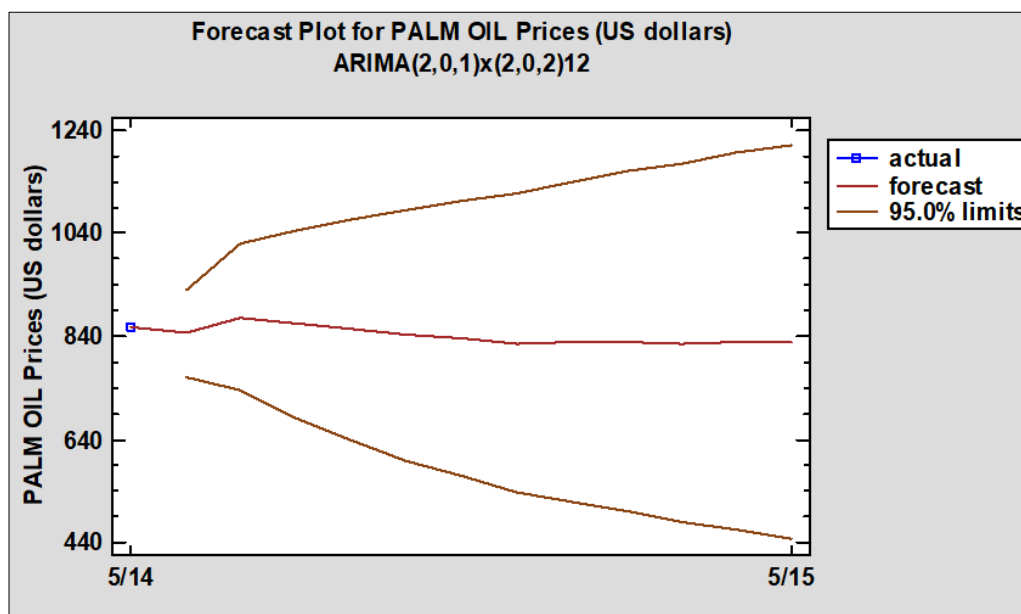


Fig 4: Forecast Plot for Monthly Palm Oil Price in Nigeria

Figure 4 shows the forecasted values of palm oil price. Also included on the plot are 95.0% prediction limits for the forecasts. These limits show where the true value of palm oil price at any point in the future is likely to be with 95.0% confidence.

4.7 Discussion of Findings

The findings from the SARIMA(2,0,1)x(2,0,2)₁₂ model selection for forecasting palm oil prices in Nigeria reveal several key insights about the underlying data and the effectiveness of the model. The significance of most parameters in the model particularly the first autoregressive

term (AR(1)), the moving average term (MA(1)), and all seasonal terms—suggests that both past values and seasonal patterns play crucial roles in predicting future palm oil prices. The AR(1) term, with a highly significant t-value and near-zero p-value, indicates a strong correlation between the current price and its immediate past value. However, the second autoregressive term (AR(2)) is not statistically significant, implying that further lags do not contribute much to improving the model's accuracy. The negative and significant coefficients for the seasonal terms (SAR(1), SAR(2), SMA(1), and SMA(2)) highlight the importance of seasonality in the price data, with pronounced cyclical

patterns likely driven by external factors such as harvest cycles or market demand fluctuations.

In terms of model performance, the relatively low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values indicate that the model is reasonably accurate in predicting palm oil prices, with an average error of about \$26.71. The Mean Absolute Percentage Error (MAPE) of 4.78% suggests that the model's predictions are typically within 5% of the actual prices, which is quite precise for economic forecasting. The minimal bias indicated by the near-zero Mean Error (ME) and Mean Percentage Error (MPE) further supports the model's reliability. However, the estimated white noise variance and standard deviation suggest that there is still a degree of randomness or unexplained variability in the data, which the model does not capture. This might point to the presence of external shocks or market anomalies that are not accounted for by the SARIMA structure. Overall, while the model performs well, there may be room for improvement by incorporating additional variables or refining the model to better capture the unexplained variance.

5. Conclusion

This chapter presents a detailed discussion of the findings from the analysis of monthly palm oil prices in Nigeria. It synthesizes the results, draws conclusions, and offers recommendations for policymakers, stakeholders, and future research. The chapter is structured into sections discussing the findings, the implications of these findings, and the limitations of the study, followed by recommendations and conclusions.

The analysis of monthly palm oil prices in Nigeria from January 1960 to May 2024 revealed significant variability in prices, with an average price of \$532.58 and a high coefficient of variation of 52.27%. The distribution of prices exhibited substantial skewness and kurtosis, indicating the presence of extreme values and a non-normal distribution. The SARIMA(2,0,1)x(2,0,2)₁₂ model was selected as the most appropriate for forecasting these prices, with key parameters such as AR(1), MA(1), and all seasonal terms showing high statistical significance. The model performed well, with low RMSE, MAE, and MAPE values, indicating accurate and reliable predictions, though some unexplained variability remained.

The study concludes that palm oil prices in Nigeria are subject to considerable fluctuations, influenced by both immediate past values and strong seasonal patterns. The selected SARIMA model effectively captures these dynamics, providing a robust tool for forecasting future prices. However, the presence of unexplained variability suggests that external factors not included in the model may also play a role in influencing price movements. This highlights the complex nature of the palm oil market in Nigeria, which is likely affected by a combination of domestic production cycles, international market trends, and other macroeconomic variables.

The findings of this study have important implications for policymakers, agricultural stakeholders, and market participants in Nigeria. Understanding the significant variability and seasonality in palm oil prices can help in the formulation of policies aimed at stabilizing the market and protecting both producers and consumers from price shocks. The ability to accurately forecast prices using the SARIMA model can also assist in strategic planning, inventory management, and decision-making within the palm oil industry.

Based on the findings, several recommendations can be made:

The government should consider implementing policies that mitigate the impact of extreme price fluctuations, such as price stabilization funds or strategic reserves.

Stakeholders should explore diversifying income sources to reduce reliance on palm oil prices, which are subject to high volatility.

There is a need for more comprehensive data collection, including variables that capture external shocks and market anomalies, to enhance the accuracy of forecasting models.

Agricultural extension services should focus on educating farmers about market trends and the importance of timing in planting and harvesting to take advantage of seasonal price variations.

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