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Palm Oil Production Forecasting Using the SARIMA Model at the Terantam Plantation of PTPN IV Regional III in 2025

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Abstract

Palm oil is a key plantation commodity that plays a major role in Indonesia's economy by contributing significantly to state revenue. Accurate forecasting of palm oil production is essential to support effective production planning and operational decision-making in plantation management. This study aimed to forecast palm oil production at the Terantam Plantation, Indonesia, for the year 2025 using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The data used consisted of monthly palm oil production volumes (kg) from January 2014 to December 2024. Several SARIMA models were evaluated, and the best-performing model was selected based on the Akaike Information Criterion (AIC). The results indicate that the SARIMA$(0,1,4)(0,1,1)_{12}$ model achieved the lowest AIC value and satisfied diagnostic requirements, with residuals behaving as white noise and following a normal distribution. The forecasting accuracy assessment yielded a Mean Absolute Percentage Error (MAPE) of 8.02%, which is below the 10% threshold and indicates very high forecasting accuracy. The forecasting results reveal a clear seasonal pattern in palm oil production, with the highest predicted production occurring in September 2025 at 15,108,145 kg and the lowest in February 2025 at 9,347,573 kg. Overall, the findings demonstrate that the SARIMA model effectively captures both trend and seasonal components of palm oil production data. The results provide valuable insights for plantation-level production planning and highlight the applicability of SARIMA-based forecasting methods for other agricultural commodities with strong seasonal characteristics.

Keywords: Palm oil, forecasting, time series, SARIMA model

1. Introduction

Palm oil (Elaeis guineensis Jacq.) is a key agricultural commodity that plays an important role in Indonesia's economy, as it supplies vegetable oil for various industrial sectors and contributes significantly to national revenue (Badan Pusat Statistik Indonesia, 2024). Globally, palm oil is the highest-producing oil crop in terms of total production volume, making it a strategic commodity in both domestic and international markets (Descals *et al*., 2024). In Indonesia, palm oil plantations are widely distributed, with Riau Province ranking among the largest producers due to its extensive plantation area and favorable agroclimatic conditions, according to Direktorat Jendral Perkebunan (2021).

One of the major state-owned enterprises engaged in the palm oil agro-industry is PTPN IV Regional III, which manages several plantation units across Riau Province. Among these, Terantam Plantation, located in Kampar Regency, represents an important production center contributing to regional and national output. Palm oil production at the plantation level directly affects operational efficiency, revenue stability, and long-term sustainability. Therefore, maintaining stable and optimal production levels is crucial for supporting effective plantation management.

Accurate production forecasting is an essential component of agricultural planning, as it enables managers to anticipate future output, optimize harvesting schedules, allocate labor and resources efficiently, and reduce operational risks. Forecasting is defined as the process of estimating future conditions based on historical data patterns and relevant influencing factors (Chaowai & Chutima, 2024). In the context of time series analysis, production data often exhibit trend and seasonal components, which must be properly modeled to obtain reliable forecasts.

Among various time series forecasting techniques, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model has been widely applied to data characterized by both trend and seasonality. The SARIMA model extends the ARIMA framework by incorporating seasonal autoregressive and moving average components, allowing it to capture recurring seasonal fluctuations more effectively (Jamila, Siregar, & Yunis, 2021). This makes SARIMA particularly suitable for modeling agricultural production data, which are strongly influenced by seasonal harvest cycles and environmental conditions.

Although previous studies have applied SARIMA models to various agricultural and industrial forecasting problems, limited research has focused on plantation-level palm oil production forecasting using long-term monthly data in Indonesia. In particular, empirical studies that provide detailed diagnostic evaluation and forecasting accuracy assessment at the estate scale remain scarce. Addressing this gap is important, as plantation-level forecasts offer more practical value for operational decision-making than aggregated regional or national forecasts.

Therefore, this study aimed to forecast palm oil production at Terantam Plantation, Indonesia, for the year 2025 using the SARIMA modeling approach. By utilizing monthly production data from January 2014 to December 2024, this research seeks to identify the most appropriate SARIMA model based on statistical criteria and diagnostic tests. The findings are expected to provide a reliable forecasting reference for plantation management and to demonstrate the applicability of SARIMA models for agricultural commodities with strong seasonal characteristics.

2. Literature Review

2.1 Palm Oil Production

Palm oil (Elaeis guineensis) is the most productive and widely traded oil crop in the world, contributing more than one-third of global vegetable oil production (Murphy, Goggin, & Paterson, 2021). Its high yield per hectare and broad industrial applications make palm oil a strategically important commodity for many producing countries, particularly Indonesia. Beyond its contribution to export earnings, the palm oil sector supports employment generation, agro-industry development, and regional economic growth (Rifin *et al*., 2020).

Palm oil production refers to the total output derived from harvested Fresh Fruit Bunches (FFB), which is influenced by multiple factors, including climatic conditions, plantation management practices, soil fertility, and plant age. Seasonal variations in rainfall and harvesting cycles often lead to fluctuations in monthly production levels. As a result, production data typically exhibit trend and seasonal patterns that require appropriate analytical approaches.

Monitoring and forecasting palm oil production are essential for plantation-level planning, as accurate forecasts enable managers to optimize harvesting schedules, manage labor allocation, and reduce uncertainty in supply chain operations. In this study, palm oil production data are measured in kilograms (kg) and obtained from historical plantation records, providing a reliable time series for analyzing production dynamics over time. Given the seasonal nature of palm oil harvesting, time series forecasting models that explicitly account for seasonality are particularly relevant.

2.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension of the Autoregressive Integrated Moving Average (ARIMA) framework that incorporates seasonal components to capture recurring patterns in time series data. While the ARIMA model effectively models non-seasonal trends through autoregressive (AR), differencing (I), and moving average (MA) components, it is limited in handling systematic seasonal fluctuations commonly observed in agricultural production data (Wei, 2006).

$$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + a_t \tag{1}$$

The SARIMA model addresses this limitation by introducing seasonal autoregressive and moving average terms, allowing both short-term dynamics and seasonal behavior to be modeled simultaneously. A SARIMA model is generally denoted as SARIMA $(p,d,q)(P,D,Q)_S$, where p,d,qrepresent the non-seasonal AR, differencing, and MA orders, while P,D,Qdenote the corresponding seasonal components with seasonal period S.

Several studies have demonstrated the effectiveness of SARIMA models in forecasting time series data with strong seasonal characteristics, including applications in agriculture, energy demand, rainfall prediction, and transportation systems (Latief et al., 2022; Febiola et al., 2024). Compared to simpler methods such as moving averages or exponential smoothing, SARIMA offers greater flexibility in capturing complex temporal structures, particularly when long-term historical data are available.

However, despite its widespread application, the effectiveness of SARIMA models depends on proper model identification, stationarity testing, parameter estimation, and diagnostic checking. In plantation-level studies, careful evaluation of residual behavior and forecasting accuracy is essential to ensure that the selected model provides reliable and actionable results. This study adopts the SARIMA modeling framework due to its suitability for monthly palm oil production data, which exhibit both trend and annual seasonal patterns.

By focusing on plantation-scale production forecasting using long-term monthly data, this research contributes to the existing literature by demonstrating the practical applicability of SARIMA models in supporting operational decision-making within the palm oil sector.

Meanwhile, the Moving Average (MA) model is a component that indicates the dependence between the current error term and the error terms from previous periods (Jamila, Siregar, & Yunis, 2021). This model is denoted as MA(q) or ARIMA(0, 0, q), and the model equation is expressed as follows (Wei, 2006).

$$Z_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \tag{2}$$

The ARIMA (Autoregressive Integrated Moving Average) model is a combination of the AR, I, and MA components. The Integrated (I) component is used to address non-stationarity in the mean of time series data by applying differencing until the data become stationary. In general, the ARIMA(p, d, q) model can be expressed in the following equation (Wei, 2006).

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t \tag{3}$$

The ARIMA model is not yet able to capture seasonal patterns that appear in time series data; therefore, it was extended to the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which combines the ARIMA components with seasonal components to model both trend and seasonal patterns in the data. The generalized ARIMA model for data with seasonal patterns is denoted as $\mathrm{SARIMA(p,d,q)(P,D,Q)}^S$. In general, the equation for the SARIMA model is expressed as follows (Wei, 2006):

$$\Phi_P(B^S)\phi_p(B)(1-B)^d(1-B^S)^D Z_t = \theta_q(B)\Theta_Q(B^S)a_t \tag{4}$$

where:

p, d, q : orders of the non-seasonal AR, differencing, MA components;
P, D, Q : orders of the seasonal AR, differencing, MA components;
Z_t : value of the variable at time *t*;
S : seasonal period;
$\phi_p(B)$: non-seasonal AR operator of order *p* = $(1 - \phi_1(B) - \cdots - \phi_p(B^p)$;
$\Phi_P(B^S)$: seasonal AR operator of order *P* = $(1 - \phi_1(B) - \cdots - \phi_p(B^{PS})$;
$(1-B)^d$: non-seasonal differencing operator of order *d*;
$(1-B^S)^D$: seasonal differencing operator of order *D*;
$\theta_q(B)$: non-seasonal MA operator of order *q* = $(1 - \theta_1(B) - \cdots - \theta_q(B^q)$;
$\Theta_Q(B^S)$: seasonal MA operator of order *Q* = $(1 - \Theta_1(B) - \cdots - \Theta_Q(B^{PS})$;
a_t : error term at time *t*.

2.3 Stationarity Test

2.3.1 Stationary in Mean

Stationarity in the mean can be examined using the Augmented Dickey-Fuller (ADF) test to remove trends or seasonal patterns in the data until the series becomes stationary. If the data are found to be non-stationary, differencing must be applied, which involves calculating the difference between the current data value and the value of the previous period (Budianti *et al*., 2024). The hypotheses used in this test are as follows (Suparti & Santoso, 2023):

H_0: $\Phi = 1$ (Data is non-stationary in mean)
H_1: $\Phi < 1$ (Data is stationary in mean)
Significance level: $\alpha = 0{,}05$
Dickey-Fuller test statistic:

$$t = \frac{\hat{\Phi} - 1}{SE_{\hat{\Phi}}} \tag{5}$$

where:

t : calculated *t*-value;
$\hat{\Phi}$: estimated value of the parameter Φ;
$SE_{\hat{\Phi}}$: standard error of Φ;

with

$$\widehat{\Phi} = \frac{\sum_{t=S+1}^{n} Z_{t-S} Z_t}{\sum_{t=S+1}^{n} Z_{t-S}^2} \tag{6}$$

$$SE_{\widehat{\Phi}} = \sqrt{\frac{\hat{\sigma}_a^2}{\sum_{t=S+1}^{n} Z_{t-S}^2}} \tag{7}$$

$$\hat{\sigma}_a^2 = \frac{1}{n-S-1} \sum_{t=S+1}^{n} (Z_t - \widehat{\Phi} Z_{t-S}) \tag{8}$$

The decision-making process is determined by comparing the ADF test statistic with the ADF critical value. If $ADF_{statistic} < ADF_{critical}$, then H_0 is rejected, which means that the data are stationary in the mean. Conversely, if $ADF_{statistic} \geq ADF_{critical}$, then H_0 is not rejected, indicating that the data are not stationary and therefore require differencing. Differencing is performed by transforming the data through subtracting the value of the previous period from the current value. In general, the differencing process for seasonal differencing with a seasonal period (S) can be written as follows (Wei, 2006):

$$1 - B^S Z_t = Z_t - Z_{t-S} \tag{9}$$

where:
Z_t : value of the time series at period *t*;
B : backshift operator, such that $B^S Z_t = Z_{t-1}$;
S : length of the seasonal period;
Z_{t-S} : value of the time series at period *t-S* (difference S of the previous period).

2.3.2 Stationary in Variance

The stationarity test in variance is conducted to examine whether the data exhibit non-constant variance, as such a condition may reduce model accuracy and cause fluctuations that cannot be predicted consistently. Non-constant variance is commonly referred to as heteroscedasticity. The stationarity test in variance is carried out using the Box-Cox transformation by observing the lambda (λ) alue obtained from RStudio. If the λ value is close to or equal to 1, the data are considered stationary in variance. Conversely, if the λ value is not close to 1 or is far from 1, the data are not yet stationary in variance.

If the data are not stationary in variance, a Box-Cox transformation will be applied to make the variance stationary. The Box-Cox transformation can be expressed as follows.

$$T(Z_t) = \begin{cases} \frac{Z_t^{\lambda} - 1}{\lambda}, & (\lambda) \neq 0 \\ ln\,(Z_t), & (\lambda) = 0 \end{cases} \tag{10}$$

where:
Z_t : actual data at time *t*;
$T(Z_t)$: Box-Cox transformation value of the data;
λ : Box-Cox transformation parameter.

2.4 lnitial Model Identification

Initial model identification is conducted by examining the data pattern using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plot is used to indicate the presence of Moving Average (MA) components, while the PACF plot is used to identify Autoregressive (AR) components (Liu *et al*., 2024). These plots assist in determining the appropriate orders of the AR and MA components in the SARIMA model. In general, initial model identification is performed through the interpretation of ACF and PACF plots. However, in this study, the auto.arima() function from the forecast package in RStudio was employed. This function automatically selects the most suitable SARIMA model by evaluating parameter combinations based on an information criterion, namely the Akaike Information Criterion (AIC).

2.5 Significance Testing of Parameters

Significance testing of model parameters is required to ensure that the parameters of the AR, MA, and seasonal components have a significant effect on the palm oil production data (kg). The hypothesis testing for parameter

significance is formulated as follows.
H_0: $\theta = 0$ (the parameter is not significant)
H_1: $\theta \neq 0$ (the parameter is significant)
Significance level: $\alpha = 0.05$
Test statistic for the parameter:

$$t = \frac{\hat{\theta}}{SE_{\hat{\theta}}} \quad (11)$$

$$\hat{\theta} = \frac{\sum_{t=1}^{n} Z_t Z_{t-1}}{\sum_{t=1}^{n} Z_{t-1}^2} \quad (12)$$

$$SE_{\hat{\theta}} = \sqrt{\frac{\hat{\sigma}_a^2}{\sum_{t=1}^{n} Z_{t-1}^2}} \quad (13)$$

$$\hat{\sigma}_a^2 = \frac{1}{n-1} \sum_{t=1}^{n} (Z_t - \hat{\theta} Z_{t-2})^2 \quad (14)$$

where:
$\hat{\theta}$: the estimated parameter being tested;
$SE(\hat{\theta})$: the standard error of $(\hat{\theta})$.

The significance test is carried out by comparing $t_{statistic}$ with $t_{\left(\frac{\alpha}{2},n-k\right)}$. If $t_{statistic} > t_{\left(\frac{\alpha}{2},n-k\right)}$, then H_0 ditolak yang berarti parameter tersebut terbukti signifikan. Namun, apabila nilai $t_{statistic} < t_{\left(\frac{\alpha}{2},n-k\right)}$, then H_0 is rejected, indicating that the parameter is significant. However, if $t_{statistic} > t_{\left(\frac{\alpha}{2},n-k\right)}$, then H_0 is not rejected, indicating that the parameter is not significant.

2.6 Diagnostic Checking

Model diagnostic testing is carried out to ensure that the selected model is appropriate for forecasting (Budianti *et al*., 2024). The diagnostic tests on the residuals include the white noise test and the normality test of the residuals.

2.6.1 White Noise Test

The White Noise test is conducted to ensure that the residuals are random and do not exhibit autocorrelation, using the Ljung–Box test. The hypotheses for the White Noise test are as follows.
H_0: residuals are white noise/random
H_1: residuals are not white noise/random
Significance level: $\alpha = 0.05$
Ljung-Box test statistic:

$$Q = n(n+2) \sum_{k=1}^{k} \frac{(\hat{\rho}_k)^2}{n-k} \quad (15)$$

where:
$\hat{\rho}_k$: residuals autocorrelation coefficient at lag *k*;
k : seasonal lag;
n : number of observations.

Rejection criteria H_0 if $Q > \chi^2_{(1-\alpha,df)}$ which means that the residuals are white noise/random (have no autocorrelation).

2.6.2 Residual Normality Test

The normality test of the residuals aims to ensure that the model residuals follow a normal distribution, which is conducted using the Kolmogorov–Smirnov test. The data used in this test are standardized residuals (Konstantinou, Mrkvicka, & Myllymaki, 2025). The hypotheses for the test are as follows.
H_0: residuals are normally distributed
H_1: residuals are not normally distributed
Significance level: $\alpha = 0.05$

Kolmogorov-Smirnov test statistic:

$$D = sup_x |F_n(x) - F(x)| \tag{16}$$

where:
sup : supremum (maximu value);
$F_n(x)$: empirical cumulative distribution function;
$F(x)$: theoretical cumulative distribution function.

Rejection criteria H_0if $D < D_{table}$ which means that the residual data is normally distributed. However, if $D > D_{table}$, then it can be concluded that the residual data is not normally distributed.

2.7 Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) a measure used to evaluate the quality of a statistical model and to select the best model among several alternatives. AIC is employed to determine the most appropriate model that best represents the data while considering the number of parameters used (Febiola *et al.*, 2024). The model with the smallest AIC value is considered the best model and will be selected for forecasting using the SARIMA method. The AIC formula is as follows.

$$AIC = log\left(\frac{\sum {e_i}^2}{n}\right) + \left(\frac{2k}{n}\right) \tag{17}$$

where:
e_i : squared residual;
k : number of parameters;
n : number of observations.

2.8 Mean Absolute Percentage Error (MAPE)

MAPE is used to measure the accuracy of a forecasting model. A smaller MAPE value indicates a higher level of forecasting accuracy (Latief, Nur'Eni, & Setiawan, 2022). The formula for calculating MAPE is as follows.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{A_i - F_i}{A_i}\right) \times 100\% \tag{18}$$

where:
A_i : actual value at the i^{th} observation;
F_i : forecast value at the i^{th} observation;
n : number of observations.

MAPE provides a criterion for evaluating the performance quality of a forecasting model (Febiola *et al.*, 2024). The smaller the MAPE value, the better the model's forecasting accuracy. The evaluation criteria are presented in the following table.

Table 1. MAPE Evaluation Criteria

MAPE Value	Interpretation
< 10%	highly accurate forecasting
10-20%	good accurate forecasting
20-50%	reasonable accurate forecasting
> 50%	inaccurate accurate forecasting

3. Materials and Methods

3.1 Data and Sources

This study focused on forecasting monthly palm oil production at Terantam Plantation, PTPN IV Regional III, Indonesia, for the year 2025. The data used in this research consisted of secondary data obtained directly from the historical production records of Terantam Plantation. Specifically, the dataset comprised monthly palm oil production volumes measured in kilograms (kg) from January 2014 to December 2024, resulting in a total of 132 observations.

The use of long-term monthly data was intended to capture both trend and seasonal patterns inherent in palm oil production. All data processing, model estimation, and forecasting analyses were conducted using RStudio software (version 4.4.2). The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed as the primary forecasting method due to its capability to accommodate seasonal fluctuations commonly observed in agricultural time series data.

3.2 Analytical Procedure

The forecasting process using the SARIMA model was conducted through several sequential stages, as described below.

1) Data Input

The monthly palm oil production data from January 2014 to December 2024 were first imported into the RStudio environment. Data consistency and completeness were verified to ensure that no missing or anomalous values would affect subsequent analyses.

2) Data Pattern Identification

An initial time series plot was generated to visually examine the overall pattern of the data. This step aimed to identify the presence of trends, seasonal variations, and irregular fluctuations, which are critical for selecting an appropriate time series modeling approach.

3) Stationarity Testing

Stationarity is a fundamental assumption in SARIMA modeling. Stationarity in the mean was examined using the Augmented Dickey-Fuller (ADF) test, while stationarity in the variance was assessed using the Box–Cox transformation. If the series was found to be non-stationary in the mean, differencing was applied iteratively until stationarity was achieved. Seasonal differencing was applied where necessary to address annual seasonal effects.

4) Initial Model Identification

The initial structure of the SARIMA model was identified through an examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots were used to determine plausible orders of the non-seasonal and seasonal autoregressive and moving average components. To support and validate this process, the auto.arima() function from the forecast package in R was also employed to generate candidate models based on information criteria.

5) Model Selection

The selection of the best-fitting model was based primarily on the Akaike Information Criterion (AIC). Among the competing models, the model with the smallest AIC value was selected, as it represents the optimal balance between model goodness-of-fit and model complexity.

6) Parameter Estimation and Significance Testing

After selecting the optimal SARIMA model, parameter estimation was performed to obtain the coefficients of the autoregressive, moving average, and seasonal components. The statistical significance of each estimated parameter was evaluated using z-tests at a 5% significance level. Parameters with p-values less than 0.05 were considered statistically significant.

7) Diagnostic Checking

Diagnostic checking was conducted to assess the adequacy of the selected model. The Ljung–Box test was applied to the model residuals to verify the absence of autocorrelation and to confirm that the residuals behaved as white noise. In addition, the normality of the residuals was evaluated using the Kolmogorov–Smirnov test. These diagnostic tests ensured that the underlying assumptions of the SARIMA model were satisfied.

8) Model Evaluation

The forecasting performance of the selected SARIMA model was evaluated using the Mean Absolute Percentage Error (MAPE). MAPE was chosen as it provides an intuitive measure of forecasting accuracy by expressing the average prediction error as a percentage of the actual values.

9) Forecasting

Finally, the validated SARIMA model was used to generate forecasts of monthly palm oil production for the period January to December 2025. The forecast results were presented along with confidence intervals to account for uncertainty in the predictions.

4 Results and Discussion

4.1 Descriptive Analysis

This descriptive analysis is used to describe the characteristics of palm oil production data based on volume (kg) at Terantam Estate by examining the mean and median values, as presented in the table below.

Table 2. Descriptive Statistics of Palm Oil Production Volume (kg)

Minimum	Q1	Mean	Median	Q3	Maximun
3,228,770	7,019,275	9,947,132	9,811,945	12,609,102	16,474,930

Table 1 shows that mean palm oil production (kg) at Terantam Estate from January 2014 - December 2024 is 9,947,132 kg, while the median is 9,811,945 kg. This indicates that there are several periods with higher production levels, resulting in the mean value being greater than the median. The minimum recorded palm oil production is 3,228,770 kg, while the maximum reaches 16,474,930 kg, indicating a considerable production gap of 13,246,160 kg.

In addition, the first quartile (Q1) is 7,019,275 kg, indicating that 25% of the palm oil production data falls below this value. Meanwhile, the third quartile (Q3) is 12,609,102 kg, showing that 75% of the production data is below this value, or only 25% of the palm oil production exceeds it. Therefore, it can be concluded that palm oil production at Kebun Terantam tends to be relatively stable, with the mean being fairly close to the median, although there are certain periods that show significant increases. The considerable range between the minimum and maximum production also reflects differences in harvest outcomes influenced by seasonal factors, weather conditions, and technical aspects of plantation management. Overall, this data indicates that production levels remain relatively high despite some fluctuations.

4.2 Data Pattern Identification

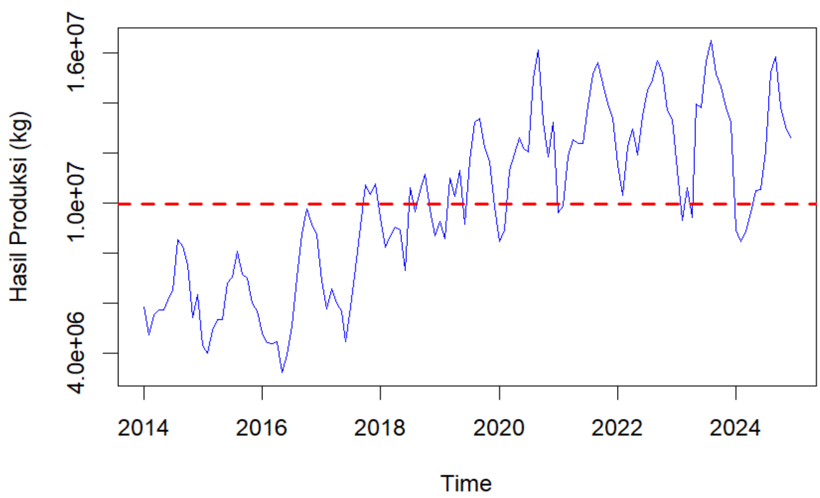

Figure 1. Plot of Palm Oil Production at Kebun Terantam

Figure 1 illustrates the pattern of palm oil production in terms of volume (kg) from January 2014 - December 2024 at Kebun Terantam. The data exhibit trends, seasonality, and random fluctuations. In general, palm oil production at Kebun Terantam has increased year by year. It can be observed that in 2019, the data pattern was around the average, while in other years, clear variations are evident.

Furthermore, Figure 4.1 also shows a recurring seasonal pattern each year, with sharp increases and decreases. This seasonal pattern can be seen through the blue line, which forms an annual repeating cycle, where production tends to decline during certain periods and then rise again in the following months. For instance, in 2024, palm oil production decreased at the beginning of the year, then increased significantly in mid-year, and declined again toward the end of the year. The consistent peaks and troughs reinforce the existence of an annual seasonal pattern in palm oil production. This pattern may be influenced by harvest cycles or environmental factors, such as rainfall and fertilization. Therefore, the SARIMA model is suitable for forecasting palm oil production at Kebun Terantam for 2025.

4.3 Stationarity Test

4.3.1 Stationarity in Mean

Stationarity in mean was tested using the Augmented Dickey-Fuller (ADF) test. This test was conducted to ensure that the data are stationary in mean. The results of the ADF test are presented in the following table.

Table 3. Stationarity Test in Mean (ADF)

Test Statistic	Lag	*p-value*	Conclusion
-4.2818	5	0.01	Reject H_0

The hypotheses for testing stationarity in mean using the Augmented Dickey-Fuller (ADF) test are as follows.
H_0: $\Phi = 1$ (Data is non-stationary in mean)
H_1: $\Phi < 1$ (Data is stationary in mean)
Significance level: $\alpha = 0.05$
Test statistic: $t = -4.2818$

By comparing the ADF test statistic with the critical value, it can be seen that $ADF_{statistic}(-4.2818) < ADF_{table}(-3.452)$, so H_0 is rejected. This indicates that the data are stationary in mean. The ADF test used a lag of 5, which represents the number of lagged residuals considered to address potential autocorrelation, making the ADF test results more accurate.

4.3.2 Stationarity in Variance

The stationarity in variance was tested using the Box-Cox transformation by examining the lambda (λ) value.

Table 4. Stationarity Test in Variance (Box-Cox Transformation)

Transformation Box-Cox	
λ	0.825

Based on Table 3, the obtained λ value is 0.825. Since this value is close to 1, it can be concluded that the data are already stationary in variance and do not require significant transformation.

4.4 Initial Model Identification

In the initial model identification stage, ACF and PACF plots were used to determine the preliminary model regarding the relevant AR and MA orders for constructing the SARIMA model. The results of the model identification are shown in Figure 2.

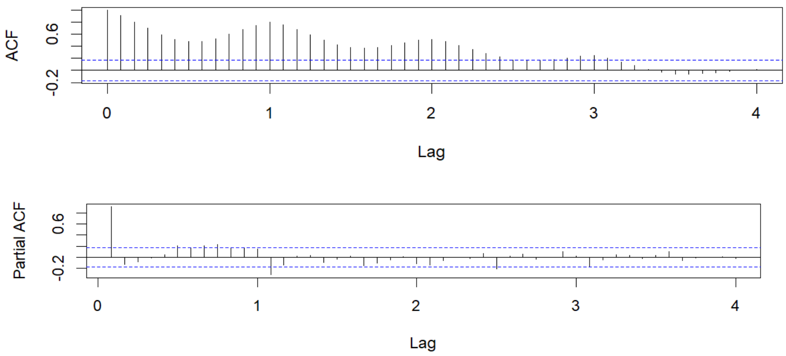

Figure 2. ACF and PACF Plots

Based on Figure 2, the ACF plot shows a gradual decline (tail-off), whereas the PACF plot exhibits a significant spike at lag 1 followed by a sharp cutoff. This pattern is characteristic of an Autoregressive (AR) model, specifically AR(0) and AR(1), as the PACF stops at lag 1. Meanwhile, the ACF plot shows a slow decline up to lag 4, indicating the presence of a non-seasonal MA component with orders MA(0), MA(1), MA(2), MA(3), and MA(4), as there is a cutoff after lag 4.

Furthermore, the ACF plot shows significant peaks at multiples of lag 12, indicating the presence of a seasonal component with an annual period (s = 12). This seasonal pattern is more clearly observed in the ACF plot than in the PACF plot, suggesting a seasonal MA component of order 1, namely MA(1) at lag 12. The initial identification results indicate that the appropriate model is SARIMA(1,0,4)(0,1,1)^{12}. Subsequently, this model will be compared with the best-fitting model obtained using the auto.arima() function in RStudio.

4.5 Model Selection

The selection of the best model was carried out by comparing the Akaike Information Criterion (AIC) values for all the models tested using RStudio. Based on experiments with several models generated by the auto.arima() function, the SARIMA(0,1,4)(0,1,1)^{12} model was identified as the best model because it has the lowest AIC value compared to the other models. This model will be compared with the model obtained from the initial identification, namely SARIMA(1,0,4)(0,1,1)^{12}.

Table 5. Model Comparison

Model	AIC
SARIMA(1,0,4)(0,1,1)^{12}	3694.375
SARIMA(0,1,4)(0,1,1)^{12}	3663.502

Based on Table 4, it can be seen that the model with the lowest AIC is SARIMA(0,1,4)(0,1,1)^{12}. This model is expected to provide more accurate forecasting results. Therefore, forecasting using the SARIMA model can be carried out with this best-fitting model.

4.6 Parameter Estimation

Table 6. Parameter Estimation

	Estimate	Standard Error	z-value	Pr(> |z|)	Conclusion
MA(1)	-0.363	0.089	-4.093	0.000	Reject H_0
MA(2)	0.039	0.097	0.404	0.686	Fail to Reject H_0
MA(3)	-0.094	0.080	-1.174	0.240	Fail to Reject H_0
MA(4)	-0.253	0.084	-2.995	0.003	Reject H_0
SMA(1)	-0.718	0.134	-5.264	0.000	Reject H_0

Parameter estimation was conducted to examine the influence of each MA and SMA component in the model. Based on Table 4.4, the estimate for the MA(1) parameter has a coefficient of -0.363, indicating a negative effect of the previous period's error on the current data. The MA(2) parameter has a coefficient of 0.039, suggesting a positive effect from the error two periods ago, although the magnitude is relatively small. The MA(3) parameter has a coefficient of -0.094, showing a negative influence from the error three periods prior.

Furthermore, the MA(4) parameter has a coefficient of -0.253, also indicating a negative effect from the error four periods ago. Meanwhile, the seasonal parameter SMA(1) has a coefficient of -0.718, meaning that the seasonal error from one period ago exerts a relatively large negative impact on the current data.

Thus, the model is formed by a combination of short-term error effects across several lags and seasonal error effects. Based on the parameter estimation results, the equation for the SARIMA(0,1,4)(0,1,1)^{12} model is obtained as follows.

$$\phi_P(B)\Phi_p(B^S)(1-B)^d(1-B^S)^D Z_t = \theta_q(B)\Theta_Q(B^S)a_t$$
$$(1-B)^1(1-B^{12})^1 Z_t = \theta_q(B)\Theta_Q(B^{12})a_t$$
$$Z_t - Z_{t-1} - Z_{t-12} + Z_{t-13} = \theta_q(B)\Theta_Q(B^{12})a_t$$

$(1 - 0.363B + 0.039B^2 - 0.094B^3 - 0.253B^4) = (1 - 0.718B^{12})a_t$
$= (1 - 0.363B + 0.039B^2 - 0.094B^3 - 0.253B^4)(1 - 0.718B^{12})a_t$
$= a_t - 0.363a_{t-1} + 0.039a_{t-2} - 0.094a_{t-3} - 0.253a_{t-4} - 0.718a_{t-12} + 0.261a_{t-13} - 0.028a_{t-14} + 0.067a_{t-15} + 0.182a_{t-16}$.

Thus, the SARIMA(0,1,4)(0,1,1)^{12} model is obtained as follows:

$$Z_t = Z_{t-1} - Z_{t-12} + Z_{t-13} + a_t - 0.363a_{t-1} + 0.039a_{t-2} - 0.094a_{t-3} - 0.253a_{t-4} - 0.718a_{t-12} + 0.261a_{t-13} - 0.028a_{t-14} + 0.067a_{t-15} + 0.182a_{t-16}.$$

This model indicates that the current period's palm oil production (Z_t) is influenced by previous period values and past error components. The value of Z_{t-1} has a positive effect on the current period, whereas Z_{t-12} has a negative effect, and Z_{t-13} has a positive effect again, reflecting an annual seasonal pattern. Regarding the error components,, a_t directly affects Z_t, while the error from one month ago (-0.363a_{t-1}) has a negative effect. The error from two months ago (0.039a_{t-2}) has a small positive effect, whereas errors from three months (-0.094a_{t-3}) and four months ago (-0.253a_{t-4}) have negative effects.

The seasonal component is strongly reflected by the error from one year ago (-0.718a_{t-12}) which exerts a large negative effect. Meanwhile, the errors from one year plus one month (0.261a_{t-13}) the error from one year plus two months (-0.028a_{t-14}) has a small negative effect, the error from one year plus three months (0.067a_{t-15}) has a small positive effect, and the error from one year plus four months (0.182a_{t-16}) has a moderately significant positive effect. Overall, this model captures a combination of short-term influences and annual seasonal patterns, with the largest impact coming from the seasonal error one year ago, which is -0.718.

4.7 Significance Testing of Parameters

The significance test was conducted to determine whether the estimated parameters have an effect on the data. Based on Table 5, the hypothesis testing for the estimated parameters is as follows.

a. MA(1)
H_0: $\Theta = 0$ (the parameter is not significant)
H_1: $\Theta \neq 0$ (the parameter is significant)
Significance level: $\alpha = 0.05$
Test statistic for the parameters MA(1) = - 4.093
Because $|t_{statistic}|$|- 4.093| > $t_{table\left(\frac{0,05}{2},132-5\right)}$(1.979), then rejected H_0. It can be concluded that, at a 5% significance level, there is sufficient evidence to state that the MA(1) parameter is significant.

b. MA(2)
H_0: $\Theta = 0$ (the parameter is not significant)
H_1: $\Theta \neq 0$ (the parameter is significant)
Significance level: $\alpha = 0{,}05$
Test statistic for the parameters MA(1) = 0.404
Because $|t_{statistic}|$|0.404| < $t_{table\left(\frac{0.05}{2},132-5\right)}$(1.979), then fail to reject H_0. It can be concluded that, at a 5% significance level, there is insufficient evidence to indicate that the MA(2) parameter is significant.

c. MA(3)
H_0: $\Theta = 0$ (the parameter is not significant)
H_1: $\Theta \neq 0$ (the parameter is significant)
Significance level: $\alpha = 0.05$
Test statistic for the parameters MA(1) = - 1.174
Because $|t_{statistic}|$|- 1,174| < $t_{table\left(\frac{0,05}{2},132-5\right)}$(1.979), then fail to reject H_0. It can be concluded that, at a 5% significance level, there is insufficient evidence to indicate that the MA(3) parameter is significant.

d. MA(4)
H_0: $\Theta = 0$ (the parameter is not significant)
H_1: $\Theta \neq 0$ (the parameter is significant)
Significance level: $\alpha = 0{,}05$
Test statistic for the parameters MA(1) = - 2.995
Because $|t_{statistic}|$|- 2.995| > $t_{table\left(\frac{0.05}{2},132-5\right)}$(1.979), then rejected H_0. It can be concluded that, at a 5% significance level, there is sufficient evidence to state that the MA(4) parameter is significant.

e. SMA(1)
H_0: $\Theta = 0$ (the parameter is not significant)
H_1: $\Theta \neq 0$ (the parameter is significant)
Taraf signifikansi: $\alpha = 0.05$
Test statistic for the parameters MA(1) = - 5.264
Because $|t_{statistic}|$|- 5.264| > $t_{table\left(\frac{0.05}{2},132-5\right)}$(1.979), then rejected H_0. It can be concluded that, at a 5% significance level, there is sufficient evidence to state that the SMA(1) parameter is significant.

In general, the MA(1), MA(4), and SMA(1) parameters are significant. These parameters have a significant effect on palm oil production data in terms of volume (kg), indicating that the model used is appropriate for capturing the data pattern. Meanwhile, the MA(2) and MA(3) parameters are not significant, suggesting that the errors better represent the patterns in short-term periods. The best model obtained previously is SARIMA$(0,1,4)(0,1,1)^{12}$ which includes MA(4). The inclusion of MA(4) in the model is based on the AIC comparison, where the model with MA(4) yields the lowest AIC value among the tested models. Therefore, SARIMA$(0,1,4)(0,1,1)^{12}$ is selected as the best model, as it effectively captures the patterns in palm oil production data in terms of volume (kg).

4.8 Diagnostic Checking

4.8.1 White Noise Test

White Noise test was conducted using the Ljung-Box test to ensure that the model used is appropriate. A model is considered adequate if the residuals behave as white noise, meaning that there is no correlation in the residuals. The results of the Ljung-Box test are presented in the following table.

Table 7. Ljung-Box Test

Model	Test Statistic	Lag	p-value	Conclusion
SARIMA$(0,1,4)(0,1,1)^{12}$	16.834	12	0.156	Fail to Reject H_0

The hypothesis testing based on the Ljung-Box test is as follows.
H_0: residuals are white noise/random
H_1: residuals are not white noise/random
Significance level: $\alpha = 0.05$
Ljung-Box test statistic = 16.834
Because $Q(16.834)$ < $\chi^2_{(1-0.95,12)}$(21.026), then fail to reject H_0. It can be concluded that, at a 5% significance level, the model exhibits white noise behavior. This means that there is no autocorrelation in the residuals, indicating that the model is suitable for use.

4.8.2 Residual Normality Test

This test was conducted using the Kolmogorov-Smirnov test, as presented in the following table.

Table 8. Kolmogorov-Smirnov Test

D	p-value	Conclusion
0.084	0.310	Fail to Reject H_0

The hypotheses for the test are as follows.
H_0: residuals are normally distributed
H_1: residuals are not normally distributed
Significance level: $\alpha = 0.05$
Kolmogorov-Smirnov test statistic (D) = 0.084
Because D (0.084) < D_{table} (0.118), then fail to reject H_0. It can be concluded that, at the 5% significance level, there is sufficient evidence to state that the residuals are normally distributed.

4.9 Mean Absolute Percentage Error (MAPE)

Table 9. Mean Absolute Percentage Error (MAPE) Value

Model	MAPE Value
SARIMA(1,0,4)(0,1,1)^{12}	8.07%
SARIMA(0,1,4)(0,1,1)^{12}	8.02%

Based on the model evaluation results in Table 9 the MAPE values for both models are not significantly different. However, SARIMA(0,1,4)(0,1,1)^{12} model has a smaller MAPE value of 8.02%. According to Table 1, a MAPE value below 10% indicates a very high forecasting accuracy. Therefore, the SARIMA(0,1,4)(0,1,1)^{12} model can be considered to have a very high accuracy in forecasting palm oil production data, making it suitable to be used as a forecasting mode.

4.10 Forecasting Using SARIMA

Forecasting of palm oil production based on volume (kg) from January - December 2025 at Kebun Terantam was carried out using the best model, namely SARIMA(0,1,4)(0,1,1)^{12}. The resulting plot is shown in Figure 3.

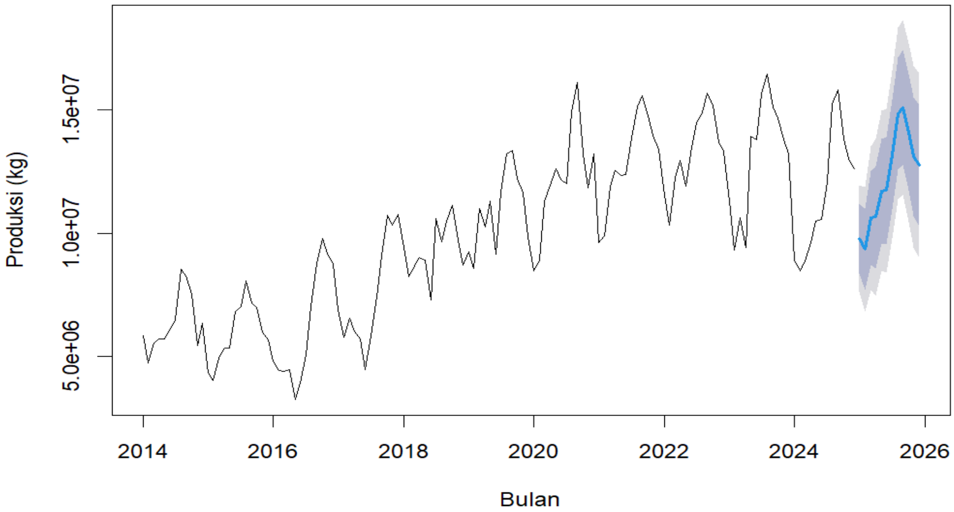

Figure 3. Forecast Plot of Palm Oil Production in 2025 at Kebun Terantam

The pattern in Figure 3 shows a seasonal variation in palm oil production that corresponds to the pattern observed in previous harvests. The forecast plot also indicates that the palm oil production trend tends to increase until mid-year and begins to decline toward the end of 2025. The shaded area in the plot represents the confidence interval, within which the forecast results fall under a certain range of uncertainty. The forecasted palm oil production for 2025 can be seen in Table 9.

Table 9. Forecasted Palm Oil Production (kg) for 2025

Month	Forecasted Value	Actual Data	Difference
January	9,784,150.00	10,086,180.00	302,030.00
February	9,347,573.00	9,876,110.00	528,537.00
March	10,610,974.00	10,398,310.00	212,664.00
April	10,652,096.00	10,964,470.00	312,374.00
May	11,710,068.00	11,850,630.00	140,562.00
June	11,724,689.00	11,312,710.00	411,979.00
July	13,177,678.00	-	-
August	14,855,589.00	-	-
September	15,108,145.00	-	-
October	14,092,335.00	-	-
November	13,114,129.00	-	-
December	12,744,594.00	-	-

Based on Table 9, the highest forecasted palm oil production occurs in September, amounting to 15,108,145.00 kg. Meanwhile, the lowest forecasted production is in February, at 9,347,573.00 kg. From January - June 2025, actual production data are available for comparison with the forecasted values. The differences between the forecasted and actual production are relatively small, such as in May 2025, where the forecasted production is 11,710,068.00 kg and the actual production is 11,850,630.00 kg, resulting in a difference of only 140,562.00 kg. This supports the previous evaluation, which indicated that the model has very high accuracy with a MAPE of 8.02%. This shows that the SARIMA(0,1,4)$(0,1,1)^{12}$ model can capture the pattern of palm oil production quite well. However, in January 2025, there is a larger discrepancy, with the forecasted value at 9,784,150.00 kg and the actual production at 10,086,180.00 kg, resulting in a difference of 302,030.00 kg. This indicates that although the model generally provides accurate forecasts, there is some variation in the level of accuracy between different months. A visualization comparing the forecasted and actual palm oil production can be seen in Figure 4.

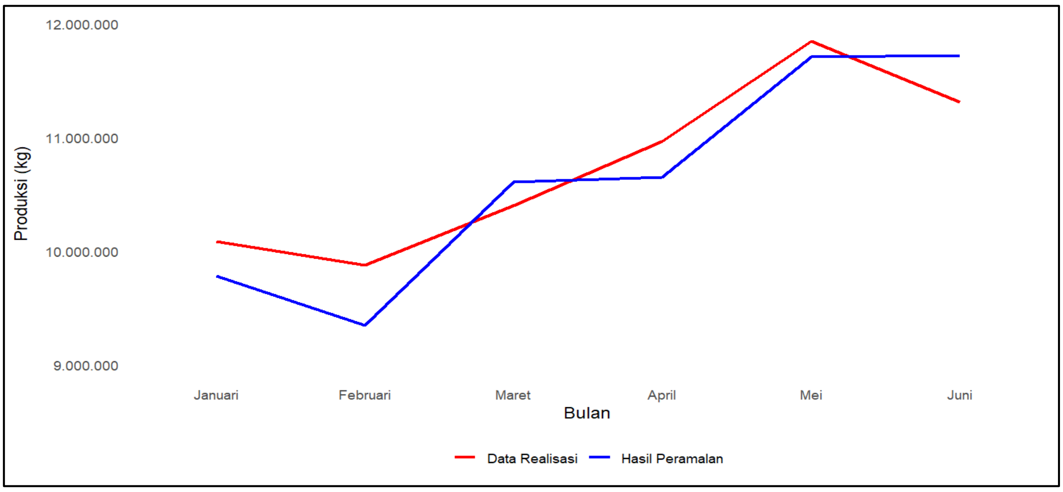

Figure 4. Forecast Plot of Palm Oil Production in 2025 at Kebun Terantam

Figure 4 shows that the comparison between the forecasted and actual palm oil production for the period January–June 2025 follows a very similar pattern. Both lines indicate a decrease in production in February, followed by an increase reaching the highest value in May, and a slight decline in June. In January and February, the actual production was recorded higher than the forecasted values. Meanwhile, from March to May 2025, the forecasted and actual production closely follow each other, with differences becoming progressively smaller, indicating a high level of model accuracy. In June, the actual production appears lower than the forecasted value, but the difference is relatively small. This demonstrates that the SARIMA(0,1,4)(0,1,1)12 model can adequately capture the fluctuations in palm oil production. Although actual data for July–December 2025 are not yet available, the forecast still provides a useful basis for production planning and decision-making regarding the optimal management strategies for Kebun Terantam.

5 Conclusion

This study demonstrated that the SARIMA(0,1,4)$(0,1,1)^{12}$ model is the most appropriate model for forecasting monthly palm oil production at Kebun Terantam, PTPN IV Regional III. The selected model effectively captured both the trend and seasonal characteristics of the production data and was subsequently used to generate forecasts for the year 2025. The forecasting results revealed a consistent seasonal production pattern, with output gradually increasing from the beginning of the year, reaching a peak in September at 15,108,145.00 kg, and declining toward the end of the year. A comparison between the forecasted values and the actual production data for January–June 2025 showed relatively small deviations, indicating good model reliability. For instance, the smallest difference occurred in May, amounting to only 140,562.00 kg, while the largest difference was observed in January at 302,030.00 kg. The forecasting accuracy evaluation yielded a Mean Absolute Percentage Error (MAPE) of 8.02%, which falls within the category of very high accuracy. This result confirms that the SARIMA model is capable of accurately representing the seasonal dynamics of palm oil production at the plantation level. From a practical perspective, the forecasting outcomes provide valuable information for plantation management, particularly in planning harvesting activities, allocating labor, and managing processing capacity. Despite its strong performance, this study is limited by the exclusion of exogenous variables such as rainfall, fertilizer application, and pest disturbances. Future research is therefore recommended to incorporate such factors using SARIMAX or hybrid forecasting approaches to further enhance predictive performance.

Overall, this study provides empirical evidence supporting the effectiveness of SARIMA modeling for seasonal palm oil production forecasting and offers a practical reference for its implementation in plantation-level decision-making.

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