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Forecasting of Palm Oil CPO Production Results at PTPN III Batang Toru Plantation Using The Autoregressive Integrated Moving Average Method

Sylva Putri Utari
Informatics Engineering
Malikussaleh University
Lhokseumawe, Indonesia
Sylva.210170247@mhs.unimal.ac.id

Asrianda
Informatics Engineering
Malikussaleh University
Lhokseumawe, Indonesia
asrianda@unimal.ac.id

Sujacka Retno
Informatics Engineering
Malikussaleh University
Lhokseumawe, Indonesia
sujacka@unimal.ac.id

Abstract— The increasing demand for palm oil as a raw material for food and energy industries has driven the need for accurate forecasting methods to optimize palm oil production management. This study aims to forecast Crude Palm Oil (CPO) production at PTPN III Batang Toru Plantation using the Autoregressive Integrated Moving Average (ARIMA) method. Monthly time series data from January 2020 to January 2024, including Fresh Fruit Bunches (FFB), loose fruit, and CPO yields, were analyzed to build the forecasting model. The Augmented Dickey-Fuller (ADF) test confirmed that the data is stationary without differencing. Based on the ACF, PACF, and white noise tests, the ARIMA(1,0,1) model was identified as the best fit. The forecasting results indicated a potential increase in CPO production from January 2025 to December 2026. However, alternative models like CPOF showed poor accuracy, with a high MAPE of 442.12%, suggesting the need for further model refinement. Despite limitations, the ARIMA method remains effective for short-term forecasting and supports data-driven decision-making in the plantation sector.

Keywords— Palm Oil, Forecasting, ARIMA, Time Series, CPO Production

I. Introduction

The development of information technology is also used as technology in the plantation sector, especially in oil palm plantations. Currently, oil palm is one of the plantation crops that has an important role in the agricultural sector, especially in the plantation sector [1]. Palm oil can be used to make vegetable oil, industrial oil, or biofuel (biodiesel). Due to the high market demand for vegetable oils such as crude palm oil and its processed products [2]. In the world, Indonesia is one of the largest producers of palm oil. The number of oil palm plantations in Indonesia has reached around 8 million hectares, double the area in 2000 and 30% of the area is on the island of Kalimantan [3].

Oil palm (Elaeis Oleifera) is a plantation crop that can produce vegetable oil in addition to nuts and corn. Oil palm fruit can be processed to produce primary products such as CPO (Dessicated Coconut Oil), PK (Dessicated Coconut Oil), and by-products such as shells, pulp, and empty bunches [4]. CPO can be used as raw material for the cooking oil, butter, and soap industries [5]. In South Tapanuli Regency, there are several palm oil factories, one of which is in Batang Toru District. Since 2010, palm oil productivity in North Sumatra has relatively increased from year to year. Although there has been a decrease in the area of oil palm plantations, productivity in South Tapanuli Regency remains unaffected, indicating the need for policies that support the potential for palm oil development, especially for community plantations.

On the other hand, the palm oil industry also faces significant challenges. Climate change, government policies, commodity price fluctuations, and debates on the environmental and social impacts of palm oil production are important in the planning and management of palm oil production in Indonesia [6]. In addition, pressure from the international market related to demands for sustainability and certification such as RSPO (Roundtable on Sustainable Palm Oil) requires industry players to adapt to new standards [7]. Therefore, the need for accurate palm oil production estimates becomes increasingly crucial because it is highly dependent on external factors that are often difficult to predict.

In this situation, developing an appropriate forecasting method becomes very important. One of the forecasting methods that is often used by experts in developing accurate palm oil production fluctuation forecasting models is the Autoregressive Integrated Moving Average (ARIMA) [8]. This method is a common choice because of its ability to handle time series data and take into account autoregression, integration, and moving average patterns [9]. The ARIMA model can analyze when the intervention starts to have an impact, how much impact the intervention has on the data, and whether the intervention will have a temporary or permanent impact in the future, as well as how the forecast results for future periods will be affected by the intervention. [10].

Based on research conducted by [11], This study aims to predict the stock prices of PT Kimia Farma Tbk and Netflix Inc during the New Normal era using the ARIMA method. Stock data is taken from Yahoo Finance, with the period 2019–2021 for Kimia Farma and 2020–2021 for Netflix. The results of the study show that the best model for Kimia Farma is ARIMA (0,1,1), but the prediction does not match the actual data because the stock price actually decreases. On the other hand, the ARIMA (1,1,1) model for Netflix shares provides fairly accurate prediction results and is in accordance with actual movements. In conclusion, the ARIMA method can be a reference for short-term predictions, but it needs to be supplemented with fundamental analysis and comparison with other prediction methods for more accurate results.

In addition, research conducted by [12], conducted research at PT Sampoerna Agro Tbk using three years of historical production data from 2015 to 2017. Their research applied various ARIMA configurations and identified ARIMA(1,1,0) as the most appropriate model based on diagnostic examination and the lowest AIC and SC values. The forecast results showed a decline in production in 2018 followed by a recovery in 2019. However, this study has limitations in terms of data coverage and does not compare ARIMA with other forecasting techniques. In addition, this study mainly focuses on climate variability as a production factor without integrating other operational or technical considerations. This leaves a gap for further research involving longer data sets, multi-model comparisons, and more comprehensive accuracy evaluations.

The purpose of this study is to design and implement a palm oil production forecasting model using the ARIMA method in order to provide more accurate production estimates in the future. With accurate forecasting, it is expected that this research can help related parties, such as farmers, plantation managers, and policy makers, in planning production strategies, distribution, and data-based decision making.

In addition, this research also aims to identify historical patterns of palm oil production and analyze the impact of various external factors that affect production fluctuations, so that strategic solutions can be formulated more precisely and adaptively to changing conditions.

II. Related Works

A. Forecasting Method

Forecasting is the art and science of predicting what will happen in the future. It can be done by involving historical data and using mathematical models to project future outcomes [13]. Forecasting methods use various mathematical models along with historical data related to forecasting and causal variables to predict demand. These models can include time series methods such as moving average, exponential smoothing, and ARIMA, or causal approaches such as linear regression that relate demand to external variables [14]. n addition to the ARIMA method, other time series-based forecasting methods include Fuzzy Time Series (FTS) and Triple Exponential Smoothing (TES). A study by Devi et al. (2024) compared these two methods in forecasting drug stock at a community health center and found that the TES method was more accurate, with a MAPE value of 9.842%, compared to the FTS Chen method, which had a MAPE of 17.67% [15]. Forecasting or prediction can be divided into three categories based on the time horizon, that are [8]:

1. Long-term forecasting, which covers a time period of more than 18 months.
2. Medium-term forecasting, which covers a time period between 3 to 18 months.
3. Short-term forecasting, which covers a time period of less than 3 months.

B. Data Mining

Data mining is the process of analyzing data to discover clear relationships and uncover previously unknown conclusions, allowing data owners to understand the information in a more current and meaningful way [16]. Data mining extracts hidden predictive information from databases. In general, there are two main categories of data processing:

1. Descriptive processing, which is the process of discovering important characteristics of the data within a single database; descriptive processing techniques include sequential processing, association, and clustering.
2. Predictive processing, which is the process of discovering data patterns by using other variables to predict future outcomes. Predictive mining uses classification as one of its methods.

Data mining can be divided into several stages as part of a sequential process. These stages are interactive, with users involved either directly or through a knowledge base. The stages include [17]:

1. Data cleaning, Data from experiments or company databases often contain incomplete entries, such as missing data, invalid data, or simple typographical errors. Additionally, there may be data features that are unrelated to the data mining hypothesis. Data cleaning also affects the performance of the data mining system, as the amount and complexity of data to be processed is reduced, and irrelevant data is discarded, which could otherwise lower the quality or accuracy of the data processing results.
2. Data integration, Features can be integrated to identify unique entities. Since errors in data integration can lead to incorrect and even misleading outcomes for future decision-making, data integration must be conducted carefully.
3. Data transformation, Some data processing methods require specific data formats before they can be applied. Certain conventional techniques, such as clustering and association analysis, can only accept categorical data. Therefore, numerical

continuous data must be divided into intervals, a process known as binning. As this transformation and data selection stage depends on certain characteristics of the data processing technique used, the quality of the subsequent data processing results is also affected by this stage.

4. Application of data mining techniques, The use of data mining techniques is just one part of the entire data mining process. There are many popular data mining methods. The next section will discuss these techniques. It is important to note that general data mining techniques available in the market are sometimes not sufficient for mining data in certain domains
5. Evaluation of discovered patterns, In this stage, the results of the data mining techniques, including unique patterns and predictive models, are evaluated to determine whether the existing hypothesis has been fulfilled. If the results do not align with the hypothesis, several actions can be taken, such as using the results as feedback to improve the data processing process, trying more appropriate data processing methods, or accepting the results as unexpected findings that may still be useful.
6. Presentation of discovered patterns for action, This is the final stage of the data mining process-making decisions or taking actions based on the analysis results. Sometimes, this involves individuals who are not familiar with data mining. Therefore, it is essential that the results of data mining are presented in a form that is understandable to everyone.

C. Autoregressive Integrated Moving Average (ARIMA)

Arima is a method that combines historical data patterns to generate forecasts. ARIMA (p, d, q) is a general term for the ARIMA process, where p denotes the order/degree of the autoregressive (AR), d is the degree of difference of the process, and q denotes the order/degree of the moving average (MA) [18]. The ARIMA (p, d, q) model is described as follows [13]:

$$B_p(B)(1-B)^d Z_t = b_0 + C_q(B)e_t \quad (1)$$

Keterangan :

Z_t	:	Observation value at time t (forecasted time series data)
B	:	Operator backshift**:** $BZ_t=Z_t-1$
d	:	Degree of differencing (component I in ARIMA)
B_p	:	Polinomial autoregressive (AR) orde p
C_q	:	Polinomial moving average (MA) orde q
e_t	:	Error (white noise) at time t
b_0	:	Constant or intercept of the model

1. Model Autoregressive

Autoregressive is a form of regression but not one that connects dependent variables but rather connects previous values at various time lags [19]. The Autoregressive (AR) model with order p is denoted by AR (p). The general form of the AR (p) model is:

$$Xt = Ø1Xt-1 + Ø2 + \cdots + ØpXt-p + \varepsilon t \quad (2)$$

Keterangan:

Xt	:	variable value at time t
$Øt$	:	variable value at time t
e_t	:	error value at time t
$Ø_p$	:	Autoregressive parameter to p =1,2,3,…,n

The level of the model is indicated by the number of historical values (p) used. The AR model, often known as AR (1) or ARIMA (1,0,0), is level one if only one past value is used.

2. Model Moving Average

The moving average model is a moving average process that is useful in describing phenomena where events produce direct effects that only last for a short period of time [20]. The moving average model process produces a q value where the moving average is denoted by MA(q). In general, the MA(q) model is:

$$Xt = \mu + et - \theta 1et - 1 - \theta 2et - 2 - \cdots - \theta qet - q \quad (3)$$

Keterangan:

Xt	:	Time series data at time t
μ	:	The mean of a process or constant in a model
e_t	:	Error (disturbance, residual, or white noise) at time t
q	:	Order of Moving Average (MA) components
θ1,θ2 ,…,θq	:	Moving Average (MA) coefficients from 1st to q order

3. Model Autoregressive Moving Average

The ARMA model is a forecasting model that is often applied to stationary time series data. This model combines two types of forecasting models, namely autoregressive regression (AR) and moving average (MA) [21]. The AR model utilizes past values of the variables to be predicted to predict future values. Meanwhile, the autoregressive moving average (ARMA) model has a structure described below:

$$Xt = \mu + \emptyset 1Xt - 1 + \cdots + \emptyset pXt - p + et - \theta 1et - 1 - \cdots - \theta qet - q \quad (4)$$

Keterangan:

Xt	:	time series data at time t
X_{t-p}	:	time series data at time period t – p, p = 1,2,3, …, n
X_{t-q}	:	error value at time t – q, q = 1,2,3,…,n
E_t	:	time error value at time t
θq	:	parameter autoregressive to q = 1,2,3, …, n
μ	:	nilai konstanta
$Ø_p$	:	parameter autoregressive to p = 1,2,3, …, n

4. Autocorrelation Function (ACF) and Partical Auto Correlation Function (PACF) function models autoregressive parameters to q

Autocorrelation coefficient (ACF) is one of the key concepts in time series analysis. ACF measures the extent to which observations at a given time (usually denoted as □□) are correlated with observations at previous times, which can be denoted as □□−1,□□−2,… ,□□-k [22]. In the context of ARIMA (Autoregressive Integrated Moving Average) analysis, ACF (Autocorrelation Function) is one of the key instruments used to identify autoregressive components in the model.

The partial autocorrelation function (PACF) is an analytical tool used to measure the degree of partial correlation between an observation at time t (denoted as Z□−1, Z□−2,…,Z□−□Z□) and observations at previous time periods. Like the autocorrelation function (ACF), the PACF is also a very important tool in time series analysis and is useful for identifying autoregressive components in ARIMA models.

Calculating and displaying the results of the autocorrelation function (ACF) and partial autocorrelation function (PACF) are needed for model identification in time series data modeling [23]. To identify the right ARIMA model, whether it is ARIMA (p,0,0) or AR (p), ARIMA (0,0,q) or MA (q), ARIMA (p,0,q) or ARMA (p,q), ARIMA (p,d,q), the results of these calculations are needed.

Table 1. Plot ACF dan plot PACF model ARIMA yang stasioner

Model	ACF	PACF
AR (p)	Drops exponentially	Cut off after lag p
MA (q)	Cut off after lag p	Drops exponentially
ARMA (p,q)	Drops exponentially	Drops exponentially

III. METHOD

The methods applied in this study include literature study, needs analysis, data collection, system design, system implementation, system testing and system evaluation. The application of this method is visualized in the form of images using the waterfall approach which will be illustrated in Figure 1 below.

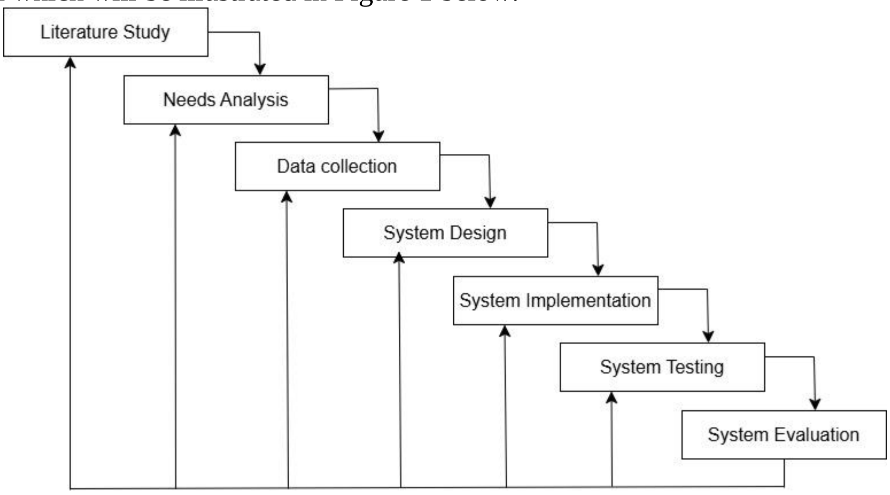

Figure 1. Research Flow Diagram

A. System Scheme

The system scheme below illustrates the work process flow of forecasting palm oil CPO production results at PTPN III Batang Toru plantation using the Autoregressive Integrated Moving Average method which is designed to help predict palm oil CPO production:

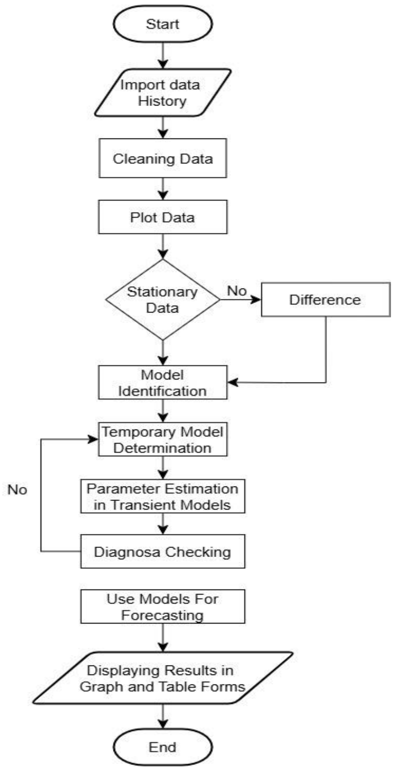

Figure 2. System Scheme

III. RESULT AND DISCUSSION

Table 2. Monthly Data

Time	Week	TBS Processed	Buah Brondolan	Result CPO
January 2025	1	1.980	316,8	435,6
	2	2.330	372,8	512,6
	3	1.950	312	429
	4	3.608	577,28	793,76
…	…	…	…	…
December 2026	1	3.475	556	764,5
	2	2.425	388	533,5
	3	4.350	696	957
	4	3.150	504	693

The data used in this study is monthly time series data from January 2020 to January 2024 which includes three main variables, namely Fresh Fruit Bunches (FFB), loose fruit, and Crude Palm Oil (CPO) yields.

A. Stationer Data

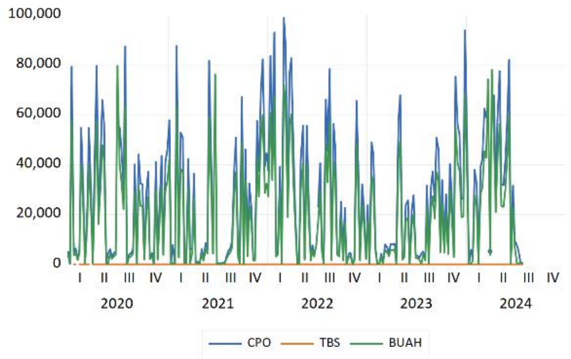

Figure 3. Data Plot

From the data plot above, it is found that the data is stationary, this diagram shows the development of production of three commodities—FFB (Fresh Fruit Bunches), CPO (Crude Palm Oil), and FRUIT—from the fourth quarter of 2021 to the fourth quarter of 2024. The blue line represents FFB, the orange line for CPO, and the green line for FRUIT. It can be seen that the volume of CPO tends to be higher than the other two commodities throughout the period, with significant fluctuations each year. Although fluctuating, the graph shows that there is generally an increasing trend from the end of 2023 to 2024, especially for CPO which peaked in the third quarter of 2024.

B. Test Unit Root

Table 3. ADF TBS Data Stationarity Test Results

Null Hypothesis: TBS has a unit root			
Exogenous: Constant			
Lag Length: 3 (Automatic – based on SIC, maxlag=14)			
		t-Statistic	Prob*
Augmented Dickey-Fuller test statistic		-4.665082	0.0001
Test critical values:	1% level	-3.459494	
	5% level	-2.874258	
	10% level	-2.573625	
*MacKinnon (1996) one-sided p-values			

Table 3 shows the results of the Augmented Dickey-Fuller (ADF) test for the actual TBS, which aims to test whether the data contains a unit root (non-stationary). The t-statistic value = -4.665082 is much smaller than the critical value at the 1%, 5%, and 10% levels, and the p-value = 0.0001, which means it is very significant. Thus, we reject the null hypothesis that TBS has a unit root, and conclude that the TBS data is stationary at the level (without the need for differentiation).

Table 4. ADF CPO Data Stationarity Test Results

Null Hypothesis: CPO has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC, maxlag=14)			
		t-Statistic	Prob*
Augmented Dickey-Fuller test statistic		-12.08575	0.0000
Test critical values:	1% level	-3.458973	
	5% level	-2.874029	
	10% level	-2.573502	
*MacKinnon (1996) one-sided p-values			

Table 4 shows the results of the Augmented Dickey-Fuller (ADF) test for actual CPO, which aims to test whether the data contains a unit root (non-stationary). The t-statistic value = -12.08575 is much smaller than the critical value at the 1%, 5%, and 10%

levels, and the p-value = 0.0000, which means it is very significant. Thus, we reject the null hypothesis that CPO has a unit root, and conclude that the CPO data is stationary at the level (without the need for differentiation).

Table 5. ADF Fruit Data Stationarity Test Results

Null Hypotesis: Fruit has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC, maxlag=14)			
		t-Statistic	Prob*
Augmented Dickey-Fuller test statistic		-12.76112	0.0000
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	
*MacKinnon (1996) one-sided p-values			

Table 5 shows the results of the Augmented Dickey-Fuller (ADF) test for actual BUAH, which aims to test whether the data contains a unit root (non-stationary). The t-statistic value = -12.76112 is much smaller than the critical value at the 1%, 5%, and 10% levels, and the p-value = 0.0000, which means it is very significant. Thus, we reject the null hypothesis that BUAH has a unit root, and conclude that the BUAH data is stationary at the level (without the need for differentiation).

C. Colegram Test

Table 6. Arima Colegram (1,0,1)

Lag	AC	PAC	Q-Stat	Prob
1	0.212	0.212	10.689	0.001
2	0.094	0.051	12.782	0.002
3	0.149	0.126	18.117	0.001
4	0.066	0.008	19.149	0.001
5	0.06	0.033	20.027	0.001
6	-0.012	-0.01	20.151	0.001
7	-0.012	-0.01	20.151	0.006
8	0.064	0.064	21.151	0.007
9	0.061	0.052	22.117	0.012
10	-0.011	0.029	23.059	0.016
11	0.09	0.089	23.887	0.013
12	0.019	0.058	24.46	0.018
13	0.025	0.018	26.052	0.017
14	0.111	0.09	29.698	0.008
15	0.132	0.086	34.069	0.003
16	-0.031	-0.106	34.314	0.003
17	0.062	0.054	35.285	0.006
18	-0.004	-0.04	35.288	0.009
19	-0.043	-0.047	35.77	0.008
20	0.032	0.03	36.033	0.009
21	-0.036	-0.021	36.371	0.02
22	0.105	0.013	39.262	0.013
23	0.095	0.028	41.612	0.011
24	-0.061	-0.096	42.597	0.014
25	-0.044	-0.063	43.11	0.017
26	-0.029	-0.064	43.346	0.02
27	-0.039	-0.012	43.765	0.022
28	-0.061	-0.032	44.769	0.021

29	-0.062	-0.04	45.809	0.02
30	-0.07	-0.036	47.125	0.02
31	-0.045	-0.052	47.862	0.021
32	-0.118	-0.109	51.476	0.016
33	-0.104	-0.024	54.024	0.018
34	0.013	0.004	54.519	0.018
35	-0.031	-0.017	54.781	0.018
36	-0.048	-0.005	55.416	0.02

Table 6 shows the residual autocorrelation test using the Autocorrelation (AC) graph, Partial Autocorrelation (PAC), and Q-Statistic values up to lag 36. The results show that at several early lags (especially lags 1 to 5), the probability value (Prob) is below 0.05, which means that the residuals still have significant autocorrelation.

D. Forecasting Data Graph

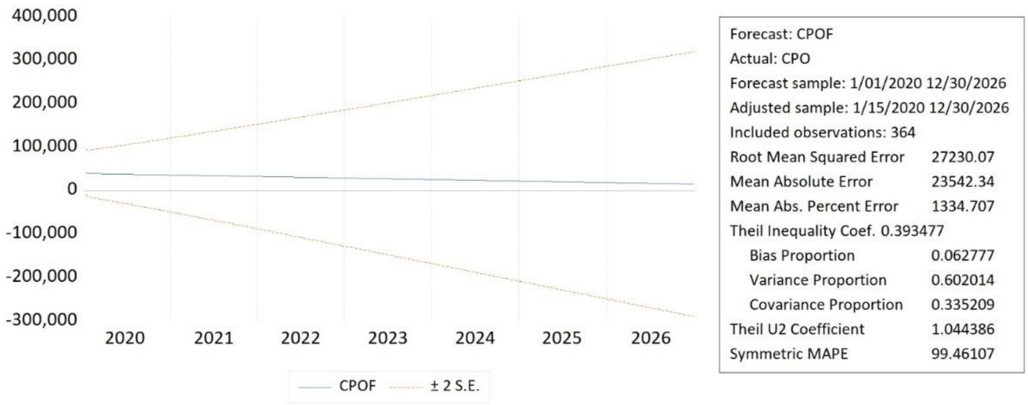

Figure 4. Forecasting Data Graph

The figure 8 shows the results of CPO value forecasting using the CPOF model for the period 1 January 2020 to 30 December 2026. The blue line shows the predicted value, while the orange dotted line shows the uncertainty limit (±2 standard error). The evaluation results show that the model has poor performance, indicated by the Root Mean Squared Error (RMSE) value of 43,611.96 and the Mean Absolute Error (MAE) of 34,156.50. In addition, the very high Mean Absolute Percent Error (MAPE), which is 442.12%, as well as the Theil Inequality Coefficient of 0.912666 and the Theil U2 Coefficient of 1.201222, indicate that the model prediction is very far from the actual data and even worse than the naive model. This CPOF model is considered inaccurate and should be re-evaluated or replaced with a more appropriate approach.

E. Data Table and Forecast Result

Table 7. Table Data and Forecast Result

Time	Week	TBS Processed	Buah Brondolan	Result CPO
January 2025	1	3.298	3.287	2.298
	2	3.300	3.288	2.292
	3	3.303	3.289	2.285
	4	3.306	3.291	2.278
…	…	…	…	…
December 2026	1	3.551	3.432	1.621
	2	3.554	3.433	1.614

3	3.553	3.435	1.608
4	3.561	3.436	1.601

The data presented is a weekly recap of palm oil production from January 2025 to December 2026, which includes the amount of FFB (Fresh Fruit Bunches) processed, loose fruit, and CPO (Crude Palm Oil) yields. There is an increasing trend in the amount of FFB processed from 3,298 tons in early January 2025 to 3,561 tons at the end of December 2026, as well as loose fruit which increased from 3,287 tons to 3,436 tons. However, the CPO yield actually showed a downward trend from 2,298 tons to 1,601 tons, indicating a decrease in the efficiency or yield of palm oil production. This decline can be caused by various factors, such as a decrease in the quality of FFB, inefficiency of the processing process, increased oil loss, weather conditions, or suboptimal harvest times. To understand the exact cause, further analysis is needed such as calculating CPO yields, evaluating fruit quality, and auditing factory processes to improve production efficiency in the future.

V. CONCLUSION

Based on the results and discussion of the Augmented Dickey-Fuller (ADF) test, all three types of data show stationary properties without the need for differentiation. The ARIMA (1,0,1) model was selected as the best model after analyzing ACF, PACF, and white noise tests. Initial evaluation of the model showed an RMSE value of 511.67 and a MAPE of 25.05%, indicating a fairly good level of accuracy for short-term forecasting. The forecasting results show a consistent upward trend in CPO production, from 26,022.22 tons in January 2025 to 28,971.45 tons in December 2026. However, further evaluation of the CPOF model showed less accurate performance with a MAPE reaching 442.12% and Theil U greater than 1, indicating that the model's prediction is worse than the naïve model. Nevertheless, the ARIMA method is still considered relevant and has the potential to be used in forecasting palm oil production, especially in the context of short-term strategic planning, as well as providing an initial overview for managerial decision making and more effective management of production results in the plantation sector.

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