P-ISSN: 2987-7261
E-ISSN: 2987-7253

Jurnal Riset Ilmu Teknik
Journal homepage: https://jurnaljepip.com/index.php/jurit
Vol. 4, No. 3, pp. 322-332, 2026
DOI: doi.org/10.59976/jurit.407

JURIT

Forecasting Palm Oil Waste Production Renewable Energy Using The Arima And Brown's Double Exponential Smoothing Methods In East Kutai And North Penajam Paser

Arini Anestesia Purba[1]*, Sahrul Januar[2], Muhammad Hudzaly Hatala[3] , Elizabeth Desfelia Ciciolini Sidabutar[4], Rimma Sianipar[5], Esther Sanda Manapa[6]

[1,2,3,4]Institut Teknologi Kalimantan, Balikpapan, Indonesia
[5]Universitas Negeri Makassar, Makassar, Indonesia
[6]Unversitas Hasanuddin, Makassar, Indonesia
Corresponding Author: arini.anestesia@lecturer.itk.ac.id

ABSTRACT

The palm oil industry in East Kalimantan generates substantial amounts of biomass waste, particularly palm kernel shells and mesocarp fiber, which have significant potential as renewable energy resources. However, the utilization of these residues remains limited due to fluctuating availability and the lack of accurate production forecasting. This study aims to compare the forecasting performance of the Auto-regressive Integrated Moving Average (ARIMA) and Brown's Double Exponential Smoothing (DES Brown) methods in predicting shell and fiber production in East Kutai and North Penajam Paser Regen-cies, and to estimate their potential for biomass-based electricity generation. Daily production data col-lected throughout 2025 were analyzed using both forecasting methods. Model performance was evaluat-ed using Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), while forecast stability was assessed through a Moving Range Chart. The results indicate that DES Brown outperformed ARIMA, achieving lower MAPE values of 0.9874% for palm kernel shells and 1.2433% for mesocarp fiber, with residuals remaining within statistical control limits. Based on the selected forecasting model, the estimated bio-mass electricity potential reached 639,409.85 MWh/year (72.99 MW) from palm kernel shells and 199,191.66 MWh/year (22.74 MW) from mesocarp fiber, resulting in a combined potential of 838,601.51 MWh/year (95.73 MW). These findings demonstrate that palm oil biomass waste can significantly con-tribute to renewable energy development and regional energy planning in East Kalimantan.

Keywords: *ARIMA, Brown's Double Exponential Smoothing, Biomass Energy, Palm Oil Waste, Forecasting.*

This is an open-access article under the CC-BY license

Manuscript received 02 September, 2026; revised 04 October 2026; accepted 17 November, 2026.

INTRODUCTION

Indonesia is the world's largest producer of palm oil, with plantation areas reaching 16.83 million hectares and crude palm oil (CPO) production of 46.82 million tons in 2022 [1]. The rapid expansion of the palm oil industry has significantly contributed to national economic growth, export revenues, and employment opportunities. However, this growth has also generated substantial quantities of biomass waste, including empty fruit bunches, palm oil mill effluent (POME), palm kernel shells, and mesocarp fiber. Among these by-products, shells and fiber possess high calorific values, making them promising renewable energy resources that can support the transition toward sustainable energy systems. Despite this potential, these biomass residues remain underutilized in many palm oil-producing regions.

East Kalimantan is one of Indonesia's major palm oil-producing provinces, with approximately 1.47 million hectares of plantation area and 18.67 million tons of fresh fruit bunch (FFB) production in 2024. Within the province, East Kutai Regency accounts for the largest plantation area, while North Penajam Paser Regency represents a medium-scale production area that is strategically important due to its proximity to the Nusantara Capital City (IKN). These

contrasting regional characteristics make both regencies suitable case studies for evaluating biomass availability and renewable energy potential from palm oil processing residues [2].

Although palm kernel shells and mesocarp fiber can be utilized as fuel for biomass power plants, briquettes, and pellets, their availability fluctuates because palm oil production is influenced by climatic conditions, market dynamics, and operational factors [3]. Consequently, accurate forecasting of biomass production is essential to ensure reliable feedstock supply for biomass-based power generation and to support effective energy planning. Without reliable forecasting, biomass utilization may become inefficient, reducing the feasibility of renewable energy investments .

Time series forecasting methods have been widely employed to estimate agricultural and industrial production. The Autoregressive Integrated Moving Average (ARIMA) model is one of the most established statistical approaches for forecasting non-stationary time series after appropriate differencing and has demonstrated strong performance in biomass and production forecasting studies. Alternatively, Brown's Double Exponential Smoothing (DES Brown) is designed for time series exhibiting linear trends and offers a computationally efficient approach by requiring only a single smoothing parameter [4], [5], [6]. Compared with methods such as the Moving Average, Naïve Method, Seasonal ARIMA, Holt–Winters, and Artificial Neural Networks, ARIMA and DES Brown provide an appropriate balance between forecasting accuracy, computational simplicity, and practical implementation for non-seasonal production data.

Several previous studies have investigated forecasting techniques or the utilization of palm oil biomass separately. Existing research has evaluated the economic feasibility of shell and fiber as boiler fuel, applied ARIMA to production and sales forecasting, and implemented exponential smoothing methods for palm oil production prediction. Other studies have compared ARIMA and DES Brown in forecasting inflation and commodity prices. Nevertheless, no previous study has simultaneously compared ARIMA and DES Brown for forecasting both palm kernel shell and mesocarp fiber production while integrating the forecasting results into an estimation of biomass-based electricity generation potential. This gap highlights the need for a comprehensive evaluation of forecasting methods that not only considers prediction accuracy but also their implications for renewable energy planning [7], [8].

This study compares the forecasting performance of ARIMA and Brown's Double Exponential Smoothing using daily production data of palm kernel shells and mesocarp fiber from East Kutai and North Penajam Paser Regencies. Forecast accuracy is evaluated using Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), while residual stability is assessed using a Moving Range Chart [9], [10]. Furthermore, the best-performing forecasting model is employed to estimate the biomass electricity potential from palm kernel shells and mesocarp fiber, providing scientific support for renewable energy development and biomass utilization strategies in East Kalimantan.

MATERIAL AND METHOD

Research Design

This study employed a quantitative research approach using time series forecasting to estimate the production of palm kernel shells and mesocarp fiber in east kalimantan. The research consisted of several sequential stages, including problem identification, literature review, data collection, data preprocessing, forecasting model development, model evaluation, biomass energy conversion, and interpretation of the results [11], [12].

Historical production data were first examined through preprocessing procedures to identify missing values, duplicate observations, and outliers [13], [14]. The cleaned dataset was then modeled using the autoregressive integrated moving average (arima) and brown's double exponential smoothing (des brown) methods [15], [16]. Forecasting performance was evaluated using several statistical accuracy measures, while forecast stability was assessed using a moving range chart [17], [18]. The best-performing forecasting model was subsequently used to estimate one-year-ahead shell and fiber production, which was then converted into biomass electricity potential. The overall research procedure is presented in figure 1.

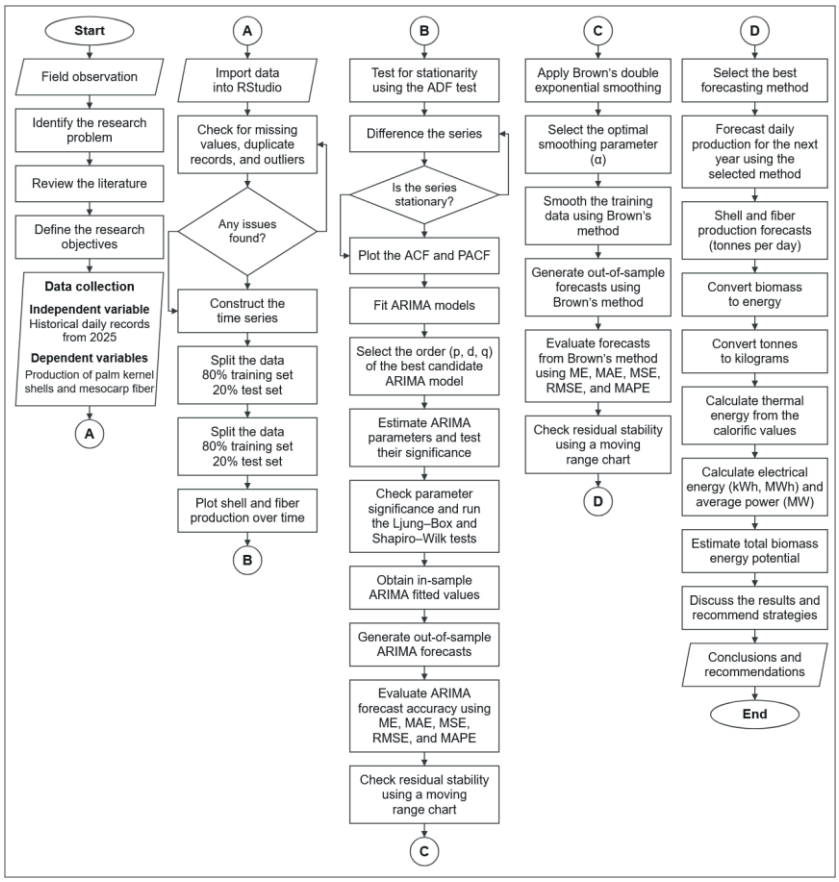

Figure 1. Research flowchart

Data Collection

This study used secondary daily time series data of palm kernel shell and mesocarp fiber production collected from January 1 to December 31, 2025. The dataset was obtained from sixteen palm oil mills located in East Kutai Regency and North Penajam Paser Regency, consisting of ten companies in East Kutai and six companies in North Penajam Paser.

The historical daily production data were aggregated according to the production date to produce a single time series for each biomass type [19]. The predictor variable consisted of historical production observations, while the response variables were daily palm kernel shell production and mesocarp fiber production. The forecasting outputs were subsequently converted into biomass electricity potential expressed in kWh, MWh, and MW [20].

Data Analysis

All analyses were conducted using RStudio because it provides comprehensive support for time series forecasting, statistical modeling, visualization, and forecast evaluation [21].

Prior to model development, the dataset was examined for missing values, duplicate records, and outliers. Outliers were identified using the Interquartile Range (IQR) method. After preprocessing, the observations were divided chronologically into 80% in-sample data for model estimation and 20% out-of-sample data for forecast validation.

For the ARIMA model, the modeling process followed the Box–Jenkins procedure consisting of stationarity testing using the Augmented Dickey–Fuller (ADF) test, differencing when required, identification of autoregressive and moving average orders through Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, parameter estimation, diagnostic checking using the Ljung–Box and Shapiro–Wilk tests, and forecasting [2], [22].

For Brown's Double Exponential Smoothing, the optimal smoothing parameter (α) was selected based on the minimum Sum of Squared Error (SSE). The fitted model was then used to generate out-of-sample forecasts [23], [24], [25].

The forecasting performance of both methods was evaluated using Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). In addition, forecast residual stability was assessed using a Moving Range Chart to determine whether the residuals remained within statistical control limits [26], [27].

Finally, forecasts generated by the selected model were converted into biomass electricity potential using the calorific values of palm kernel shells and mesocarp fiber together with a biomass power plant conversion efficiency of 25%. The resulting electrical energy was expressed in kWh, MWh, and MW to estimate the renewable electricity potential in East Kalimantan [28].

RESULTS

Data Description and Preprocessing

This study was conducted using secondary daily time-series data of palm kernel shell and palm fiber production collected from 16 palm oil processing companies, comprising ten companies located in East Kutai Regency and six companies in North Penajam Paser Regency. The dataset covers the period from January 1 to December 31, 2025. East Kutai was selected because it has one of the largest oil palm plantation areas in East Kalimantan, providing abundant and continuous biomass resources. Meanwhile, North Penajam Paser represents a medium-scale oil palm production area and plays a strategic role as a supporting region for the Nusantara Capital City (IKN). Therefore, both regions provide a representative basis for evaluating the potential utilization of palm oil waste as a renewable energy source.

Prior to forecasting model development, the data were subjected to a preprocessing stage to ensure their quality and reliability. The initial dataset consisted of 5,840 production records for each variable collected from all participating companies. Data quality assessment included checking for missing values, duplicate records, and outliers using the Interquartile Range (IQR) method. The results showed that no missing values or duplicate records were identified. In addition, all observations remained within the acceptable control limits for both palm shell and palm fiber production, indicating that the dataset was suitable for forecasting without requiring data imputation or removal of observations.

After the preprocessing stage, production data from all companies were aggregated into daily observations, resulting in 365 observations for each variable. To evaluate forecasting performance objectively, the dataset was divided sequentially into 292 in-sample observations (80%) for model development and 73 out-sample observations (20%) for model validation. This chronological data partition preserves the temporal structure of the time-series data and provides a reliable basis for assessing the forecasting accuracy of the developed models.

Identification of Time Series Pattern

Before selecting the appropriate forecasting model, the characteristics of the palm shell and palm fiber production data were examined through graphical visualization and stationarity testing. Time series plots were used to identify the presence of trends and fluctuations, while the Augmented Dickey–Fuller (ADF) test was conducted to determine whether the data satisfied the stationarity assumption required for ARIMA modeling.

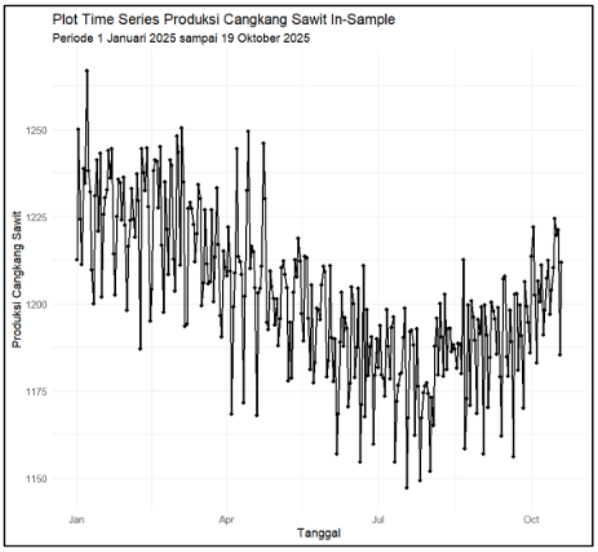

Figure 2. Time series plot of palm shell production

Figure 2 illustrates the daily production pattern of palm kernel shells during the observation period. The production level remained relatively high, ranging from approximately 1,200 to 1,250 tons/day during January to March, followed by a gradual decline to around 1,150 tons/day between April and July. Production then increased again from August until the end of the observation period. These changes in production level indicate the presence of an upward and downward trend over time, suggesting that the original shell production data were not stationary.

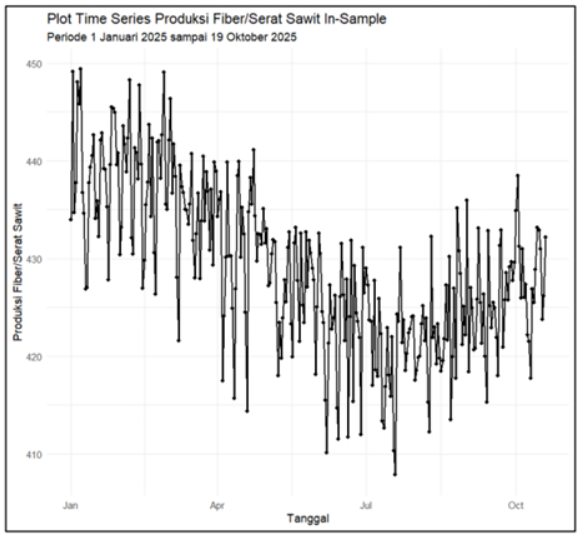

Fig 3. Time series plot of palm fiber production

A similar pattern was observed for palm fiber production, as presented in Figure 3. Daily production fluctuated within the range of approximately 410–450 tons/day. A decreasing trend was observed during the middle of the year, followed by a gradual increase toward the end of the observation period. The changing production level indicates that the mean of the series was not constant over time, implying that the original fiber production data were also non-stationary.

Table 1. Results of the Augmented Dickey-Fuller stationarity test

Variable	Differencing	Data Description	Number of Observations	ADF Statistic	ADF p-value	Decision
Shell	0	Original data	292	-1.524790	0.7764617	Non-stationary
Shell	1	1st differencing	291	-14.006925	0.0100000	Stationary
Shell	2	2nd differencing	290	-19.237549	0.0100000	Stationary
Fiber	0	Original data	292	-2.083995	0.5408037	Non-stationary
Fiber	1	1st differencing	291	-12.414728	0.0100000	Stationary
Fiber	2	2nd differencing	290	-20.060643	0.0100000	Stationary

The visual interpretation obtained from Figures 2 and 3 was further confirmed using the Augmented Dickey–Fuller (ADF) stationarity test. As presented in Table 1, the original shell and fiber production data produced p-values of 0.7765 and 0.5408, respectively, which are greater than the significance level of 0.05. These results indicate that both datasets were non-stationary and required differencing before ARIMA modeling could be performed.

After applying the first-order differencing process, the p-values for both variables decreased to 0.0100, indicating that the null hypothesis of a unit root was rejected. Therefore, the differenced series can be considered stationary and suitable for ARIMA model development. Since stationarity was achieved after the first differencing, the differencing order used in this study was determined as.

Furthermore, the stationary series fluctuated around a relatively constant mean without exhibiting a clear upward or downward trend. Based on these findings, the forecasting model was developed using the ARIMA framework, while the optimal values of the autoregressive (AR) and moving average (MA) components were determined in the subsequent modeling stage.

Forecasting Model Development

Following the identification of the time-series characteristics, forecasting models were developed using the ARIMA and Brown's Double Exponential Smoothing (DES Brown) methods. The ARIMA model was constructed using the stationary series obtained after first-order differencing, whereas DES Brown was applied directly to the original data because the method is capable of handling trend patterns without requiring stationarity. The objective of this stage was to determine the optimal model parameters before evaluating forecasting performance.

ARIMA Model

For the ARIMA approach, several candidate models were evaluated using the in-sample dataset. Model selection was based on the smallest Akaike Information Criterion (AIC), parameter significance, and residual diagnostic tests. Among the evaluated models, ARIMA(4,1,3) without drift was selected as the best model for palm shell production with an

AIC value of 2,379.158, while ARIMA(5,1,3) without drift was identified as the best model for palm fiber production with an AIC value of 1,790.247.

The parameter estimation results indicate that all autoregressive (AR) and moving average (MA) coefficients in both models are statistically significant ($p < 0.05$), suggesting that each parameter contributes meaningfully to the forecasting model. Residual diagnostics further showed that the residuals followed a normal distribution based on the Shapiro–Wilk test. However, the Ljung–Box test indicated that the residuals were not completely white noise, implying that although the models captured the main data patterns, a small amount of autocorrelation remained.

Tabel 2. Parameter Estimates and Significance Of The ARIMA Model For Shells

No	Parameter	Estimate	Std. Error	Z-Value	P-Value	Decision
1	ar1	1.1060894	0.06320105	17.501124	< 0.001	Significant
2	ar2	-1.1597066	0.08543810	-13.573648	< 0.001	Significant
3	ar3	0.2780567	0.08510912	3.267061	0.0010867	Significant
4	ar4	-0.3319854	0.06199178	-5.355313	< 0.001	Significant
5	ma1	-2.0292338	0.04264913	-47.579718	< 0.001	Significant
6	ma2	1.9908555	0.05630160	35.360551	< 0.001	Significant

Tabel 3. Parameter Estimates and Significance of the ARIMA Model For Fiber

No	Parameter	Estimate	Std. Error	Z-Value	P-Value	Decision
1	ar1	1.3118939	0.06929369	18.932372	< 0.001	Significant
2	ar2	-1.1707777	0.09637074	-12.148685	< 0.001	Significant
3	ar3	0.3981284	0.11975121	3.324629	0.0008854	Significant
4	ar4	-0.3642902	0.09561570	-3.809941	0.0001390	Significant
5	ar5	0.2207077	0.06612086	3.337944	0.0008440	Significant
6	ma1	-2.1294163	0.03610723	-58.974794	< 0.001	Significant
7	ma2	2.1075752	0.04769578	44.187880	< 0.001	Significant
8	ma3	-0.9037602	0.03479933	-25.970618	< 0.001	Significant

DES Brown Model

Brown's Double Exponential Smoothing was developed using the original production data because the method does not require stationary observations. The smoothing parameter (α) was determined by minimizing the Sum of Squared Errors (SSE) within the range of 0.01–0.99. The optimal smoothing parameter obtained for palm shell production was $\alpha = 0.049395$, whereas palm fiber production achieved an optimal value of $\alpha = 0.04706$.

The resulting DES Brown models produced smooth forecasts that followed the overall trend of the historical production data. Compared with the observed series, the forecasts successfully represented the general direction of production changes while reducing short-term fluctuations. These optimized models were subsequently evaluated and compared with the ARIMA models to determine the most accurate forecasting approach.

P erformance Comparison

To determine the most appropriate forecasting method for palm shell and palm fiber production, the performance of the ARIMA and Brown's Double Exponential Smoothing (DES Brown) models was evaluated using several forecasting accuracy measures. The comparison was based on Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). In addition, residual stability was assessed using the Moving Range Chart (MRC) to evaluate the consistency of forecasting errors.

Tabel 4. Comparison of ARIMA and DES Brown Accuracy Values

Variable	Method	Model	ME	MAE	MSE	RMSE	MAPE (%)
Shell	DES Brown	Alpha = 0.049395	-4.740367	11.960351	235.93898	15.360305	0.9874053
Shell	ARIMA	ARIMA(4,1,3) without drift	8.797350	13.500566	270.63721	16.451055	1.1037259
Fiber	DES Brown	Alpha = 0.04706	4.105550	5.450233	43.52838	6.597604	1.2433419
Fiber	ARIMA	ARIMA(5,1,3) without drift	7.326611	7.694617	78.17970	8.841929	1.7555437

As presented in Table 4, Brown's Double Exponential Smoothing consistently produced lower forecasting errors than the ARIMA model for both palm shell and palm fiber production. For palm shell production, DES Brown achieved a MAPE of 0.9874%, which was lower than the 1.1037% obtained by ARIMA. Similarly, for palm fiber production, DES Brown produced a MAPE of 1.2433%, outperforming the ARIMA model, which recorded a MAPE of 1.7555%. Since lower MAE, MSE, RMSE, and MAPE values indicate better forecasting performance, these results demonstrate that DES Brown provides more accurate forecasts than ARIMA for both variables.

The superior performance of DES Brown can be attributed to the characteristics of the production data, which exhibit a clear trend without strong seasonal fluctuations. Brown's Double Exponential Smoothing is specifically designed to model trend components through double smoothing, allowing it to adapt effectively to gradual changes in production

levels. In contrast, although ARIMA successfully modeled the data after differencing, its forecasting errors remained slightly higher than those of DES Brown.

Tabel 5. Parameter Estimates and Significance of The ARIMA Model For Fiber

Variable	Method	MR-bar	UCL	LCL	Points Outside Limits	Decision
Shell	ARIMA	13.4548	43.9569	0	1	Relatively stable
Shell	DES Brown	13.5176	44.1621	0	1	Relatively stable
Fiber	ARIMA	5.3122	17.3548	0	1	Relatively stable
Fiber	DES Brown	5.6459	18.4453	0	1	Relatively stable

Residual stability analysis further supports the forecasting results. As shown in Table 5, both forecasting methods produced relatively stable residuals, with only one observation exceeding the upper control limit for each variable. Although the ARIMA models generated slightly lower Moving Range (MR-bar) values than DES Brown, the differences were minimal and did not substantially affect model stability. Therefore, both methods can be considered statistically stable for forecasting applications.

Considering both forecasting accuracy and residual stability, Brown's Double Exponential Smoothing was selected as the best forecasting method in this study. The method consistently achieved the smallest forecasting errors while maintaining stable residual behavior. These findings indicate that DES Brown is more suitable than ARIMA for forecasting palm shell and palm fiber production under the observed data characteristics.

Forecast of Biomass Electricity Potential

After identifying Brown's Double Exponential Smoothing as the most accurate forecasting method, the selected model was used to forecast palm shell and palm fiber production for one year ahead, covering the period from January 1 to December 31, 2026. The forecasted biomass production was subsequently converted into biomass electricity potential using the conversion equations described in the methodology section. This conversion provides an estimate of the renewable energy that can be generated from palm oil processing waste.

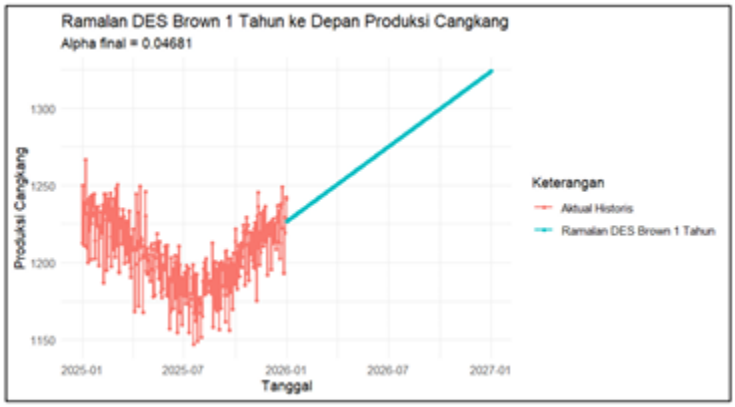

Figure 4. One year-ahead DES Brown forecast of shell production

Figure 4 illustrates the forecasted production of palm kernel shells during 2026. The forecast shows a gradual increase in production from approximately 1,226.73 tons/day at the beginning of the year to around 1,323.94 tons/day by the end of the forecasting period. This pattern indicates that shell production is expected to continue its upward trend, suggesting a stable and sustainable supply of biomass for future energy generation.

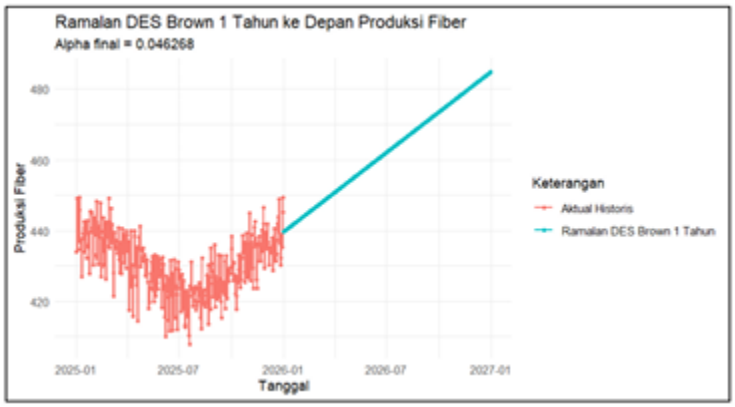

Figure 5. One-Year-Ahead DES Brown Forecast of Fiber Production

A similar increasing trend was observed for palm fiber production, as presented in Figure 9. Daily production is forecasted to increase from approximately 439.71 tons/day to 484.82 tons/day during the forecasting period. The consistent increase in fiber production further strengthens the availability of biomass resources that can complement palm shell utilization in renewable electricity generation.

The forecasted biomass production was converted into electrical energy potential by considering the calorific value of each biomass type and an assumed electricity conversion efficiency of 25%. Daily electrical energy was first calculated in kilowatt-hours (kWh) and megawatt-hours (MWh), followed by the estimation of average electrical power in megawatts (MW). The conversion process was performed for each day of the forecasting period, and the results were accumulated to obtain the annual biomass electricity potential.

Table 6. Total Biomass Electricity Potential of Palm Shells and Fiber

Component	Palm Shell	Palm Fiber	Total
Total biomass production (tons/year)	465,495.5465	168,727.0529	634,222.5994
Total electrical energy (MWh/year)	639,409.8549	199,191.6596	838,601.5145
Average daily electrical energy (MWh/day)	1,751.8078	545.7306	2,297.5384
Average annual power (MW)	72.99	22.7388	95.73

The annual biomass electricity potential derived from the forecasting results is summarized in Table 6. The total forecasted biomass production reached 634,222.60 tons/year, consisting of 465,495.55 tons/year of palm shells and 168,727.05 tons/year of palm fiber. Based on the energy conversion process, the total electrical energy potential was estimated at 838,601.51 MWh/year, equivalent to an average power generation capacity of 95.73 MW.

Palm kernel shells contributed the largest share of electricity generation, producing approximately 639,409.85 MWh/year or 72.99 MW, accounting for around 76.25% of the total biomass electricity potential. In comparison, palm fiber contributed 199,191.66 MWh/year or 22.74 MW, representing approximately 23.75% of the total potential. The higher contribution of palm shells is associated with their greater forecasted production volume and higher calorific value compared with palm fiber.

These findings demonstrate that palm oil processing waste has substantial potential to support renewable electricity generation in East Kalimantan. The forecasted availability of palm shells and fiber indicates that biomass can serve as a reliable and sustainable energy resource while simultaneously contributing to improved utilization of agricultural waste.

Utilization Strategy Recommendations

To assess its significance, this potential was compared with regional electricity demand. Electricity sold by PLN in East Kutai in 2022 amounted to 21,679,747.82 kWh/year, equivalent to an average power of 2.47 MW (BPS of East Kutai Regency, 2023); in North Penajam Paser in 2024 it amounted to 123,648,724 kWh/year, equivalent to 14.12 MW (RPJMD of North Penajam Paser Regency 2025–2029); while at the East Kalimantan Province level in 2023 it amounted to 4,506,582,606 kWh/year, equivalent to 514.45 MW (BPS of East Kalimantan Province, 2024). Thus, the biomass electricity potential of 95.73 MW is equivalent to about 38.7 times the average power of electricity sold in East Kutai and 6.8 times that of North Penajam Paser, as well as 18.61% of the provincial average power. Shell and fiber biomass energy cannot yet replace the province's entire electricity demand, but it has the potential to become a significant supporting source in the renewable energy mix while opening opportunities to channel surplus electricity to industrial estates and other regions.

The differing characteristics of the two regions call for a tiered utilization strategy from the regency to the provincial level, as summarized in Table 7.

Table 7. Recommend strategies for utilizing palm waste as renewable energy

Region	Basis from Previous Research	Recommended Strategy	Expected Impact
East Kutai Regency	Regions with a high biomass supply are more effectively developed into biomass power generation centers because feedstock continuity is better assured (Abdullah et al., 2015; Putra et al., 2018)	Development of large-scale biomass power plants (PLTBm) fueled by palm shells and fiber (Putra et al., 2018)	Increasing the renewable energy supply and reducing palm waste
East Kutai Regency	Palm biomass has a high calorific value and the potential to support regional energy security (Dewi et al., 2022)	Development of a palm biomass energy industrial estate	Increasing investment and the added value of the palm oil industry
North Penajam Paser Regency	Regions with medium biomass availability are better suited to local energy utilization and co-generation systems (Yulianti, 2020)	Utilization of shells and fiber as fuel for boilers and captive power plants	Reducing fossil fuel use in the palm oil industry
North Penajam Paser Regency	Biomass can serve as a supporting energy source in developing regions and strategic areas (BPDP, 2025)	Development of small-to-medium-scale biomass power plants (PLTBm)	Supporting local energy needs and the IKN buffer zone

East Kutai and PPU	The main obstacles to biomass development are logistics and fuel supply continuity (Suprianto, 2024)	Development of a Biomass Collection Center	Reducing logistics costs and improving the reliability of biomass supply
East Kalimantan Province	Biomass energy planning requires region-based biomass potential mapping (Dewi et al., 2022)	Preparation of a regional biomass potential map	Supporting data-driven decision-making
East Kalimantan Province	Palm biomass can support the achievement of renewable energy mix targets and the green energy transition (BPDP, 2025)	Integration of biomass into the Regional Energy General Plan (RUED)	Reducing dependence on coal
East Kalimantan Province	Pretreatments such as torrefaction and densification can increase the calorific value of biomass and combustion efficiency (Abdullah et al., 2015)	Development of biomass quality improvement technologies	Improving biomass energy conversion efficiency
East Kalimantan Province	Biomass energy development requires collaboration among the government, industry, PLN, and investors (Suprianto, 2024; BPDP, 2025)	Establishment of regional biomass energy partnerships	Accelerating the implementation of renewable energy projects

DISCUSSION

Based on daily data from 16 palm oil mills in East Kutai and North Penajam Paser, the Double Exponential Smoothing Brown (DES Brown) model produced lower forecasting errors than ARIMA. In the 73 test observations, the MAPE decreased from 1.1037% to 0.9874% for shells and from 1.7555% to 1.2433% for fiber. The improvement was greater for fiber. The Moving Range chart showed one data point outside the control limits for each combination of model and biomass type; therefore, the selection of DES Brown was primarily based on its lower error. These results are consistent with those of [25], [29], [30], who found that Holt smoothing produced slightly lower MAE and RMSE values than ARIMA for annual food production indices in Türkiye. Holt and Brown are different smoothing variants, but both studies indicate that trend smoothing can provide more accurate forecasts than ARIMA for certain production data.

Assuming a conversion efficiency of 25%, the forecasting results for shells and fibers for 2026 yield an estimated electricity potential of 838,601.51 MWh per year, equivalent to an average capacity of 95.73 MW. These findings are consistent with those of [26], who showed that utilizing residues from 28 palm oil mills in Colombia could generate a surplus of electricity under certain technological scenarios. That study also demonstrated that the magnitude of the surplus varies depending on the power plant configuration. Thus, the estimate of 95.73 MW can serve as a starting point for planning. The amount of electricity that can be transmitted must be calculated using power plant efficiency and the mills' internal electricity needs.

[12] obtained different results in forecasting post-harvest waste. In cross-validation, the ARIMA model produced a lower average RMSE than the ETS smoothing model. However, in evaluations by fruit type, the ETS model was more accurate for several groups, including berries. [11] also obtained a higher $R^{\wedge 2}$ value for ARIMA in annual cereal production in Ethiopia, while some smoothing models yielded a lower AIC. These differences indicate that model ranking depends on data patterns and the scope of evaluation. The superiority of the Brown DES on the test data in this study supports its selection for husks and fiber at the study site. The accuracy of one-year forecasts still needs to be tested with actual data from a longer period.

Differences were also observed in biomass composition. This study projected 465,495.55 metric tons of husks and 168,727.05 metric tons of fiber, with husks accounting for 76.25% of the estimated biomass. In contrast, [8] summarized that the processing of fresh fruit bunches generally yields 5.2–7% shells and 11–15% fiber by mass. Since the order is reversed, the basis for recording these two materials needs to be examined. Mill records must indicate whether the figures used include all residues produced or only those available after internal use, as well as whether both were weighed on the same moisture content basis. The results of this examination will determine the strength of the conclusion that shells are the primary source of electricity at the study site.

References [31], [32] expanded the forecasting approach in the palm oil sector by incorporating climate conditions, soil, crop age, and cultivation practices to predict harvest yields. For forecasting shells and fiber, this approach can be applied by testing whether the volume of incoming fresh fruit bunches, operating hours, and production stoppages improve the results of the Brown DES. At the utilization stage, Handaya et al. [42] demonstrated that storage, transportation, and competition for shell use affect supply continuity. Combining production forecasts per mill with internal usage and shipment data will help estimate how many metric tons of biomass a power plant can actually receive each month. This information can be used to assess the power plant capacity that aligns with the supply in each regency.

CONCLUSION

Double Exponential Smoothing Brown (DES Brown) is more accurate than ARIMA in forecasting palm kernel shell and fiber production using test data from 16 mills in East Kutai and North Penajam Paser. The DES Brown MAPE was 0.9874% for shells and 1.2433% for fiber, while the ARIMA MAPE was 1.1037% and 1.7555%, respectively. Assuming

a conversion efficiency of 25%, the projected biomass production for 2026 has the potential to generate 838,601.51 MWh of electricity per year, equivalent to an average capacity of 95.73 MW. Shells account for 76.25% of this estimate, making them the primary source in the preliminary planning of biomass supply for electricity generation in the study area.

Future research is advised to use historical data covering a longer period so that trend and seasonal patterns can be analyzed more comprehensively, to expand the study area, to compare with other forecasting methods, to validate the strategy recommendations through expert judgment, and to model non-aggregated data.

ACKNOWLEDGMENTS
The authors thank the 16 participating palm oil mills in East Kutai and North Penajam Paser regencies for providing the daily production records used in this study.

CONFLICT OF INTEREST
The authors declare no conflicts of interest related to this study.

DATA AVAILABILITY STATEMENT
The study used daily production records for palm kernel shells and mesocarp fiber from January 1 to December 31, 2025. The article presents summaries of the aggregated data and the forecasting results. Requests for the original mill-level records may be directed to the corresponding author and are subject to approval by the respective mills.

FUNDING
This study received no external funding.

DECLARATION OF AI TOOL USAGE
No AI tools were used to analyze.

REFERENCES

[1] Dinas Perkebunan Kalimantan Timur, "Data Perkebunan Provinsi Kalimantan Timur 2022," Dinas Perkebunan Kalimantan Timur, Samarinda, Indonesia, 2022.
[2] Badan Pengelola Dana Perkebunan Kelapa Sawit, "Biomassa sawit mendukung ketahanan energi berkelanjutan," 2025.
[3] Handaya, H. Susanto, D. Indrawan, and Marimin, "A Soft System Dynamic Approach for Designing Palm Kernel Shell Supply Chain," *Oper. Supply Chain Manag. An Int. J.*, vol. 15, no. 1, pp. 148–163, 2022, doi: 10.31387/oscm0480337.
[4] H. A. Yanti, "Pengolahan data sederhana menggunakan R Studio," *Sienna*, vol. 2, no. 1, pp. 1–9, 2021.
[5] W. A. Pratiwi, N. Melisa, V. A. Adistie, S. Mifthasha, and S. Putri, "Peramalan jumlah produksi kelapa sawit Provinsi Riau menggunakan metode double exponential smoothing," *Indones. Counc. Prem. Stat. Sci.*, vol. 2, no. 2, pp. 74–85, 2023.
[6] A. Puspitaningrum, S. Abadi, and I. P. E. Wijaya, "Peramalan minyak kelapa sawit dengan pemulusan eksponensial di Pabrik Kelapa Sawit Cikasungka PT. Perkebunan Nusantara VIII," *Mimb. Agribisnis*, vol. 9, no. 2, pp. 3273–3284, 2023.
[7] S. A. Sinaga, "Implementasi metode ARIMA (autoregressive integrated moving average) untuk prediksi penjualan mobil," *J. Glob. Technol. Comput.*, vol. 2, no. 3, pp. 102–109, 2023.
[8] R. Nabila *et al.*, "Oil palm biomass in Indonesia: Thermochemical upgrading and its utilization," *Renew. Sustain. Energy Rev.*, vol. 176, p. 113193, 2023, doi: 10.1016/j.rser.2023.113193.
[9] R. Dewi, U. Djufri, and H. Wijaya, "Pemanfaatan biomassa padat kelapa sawit sebagai energi baru terbarukan di PLTU Pabrik Kelapa Sawit PT Perkebunan Nusantara VI Unit Usaha Bunut," *J. Electr. Power Control Autom.*, vol. 5, no. 1, pp. 1–7, 2022.
[10] W. Budiaji, "Penerapan reproducible research pada RStudio dengan bahasa R dan paket Knitr," *Khazanah Inform.*, vol. 5, no. 1, pp. 1–5, 2019.
[11] G. Bezabih, M. Wale, N. Satheesh, S. W. Fanta, and M. Atlabachew, "Forecasting cereal crops production using time series analysis in Ethiopia," *J. Saudi Soc. Agric. Sci.*, vol. 22, no. 8, pp. 546–559, 2023, doi: 10.1016/j.jssas.2023.07.001.
[12] I. K. Opara, Y. Silue, U. L. Opara, and O. A. Fawole, "Forecasting of postharvest fresh produce waste at the wholesale level using time series models," *Agric. Food Secur.*, vol. 14, p. 24, 2025, doi: 10.1186/s40066-025-00550-3.
[13] L. F. Marini, P. Sarungallo, R. O. Pramanagara, and H. A. S. Budi, "Analisis ekonomi pemanfaatan limbah pabrik kelapa sawit sebagai bahan bakar boiler," *Igya Ser Hanjop*, vol. 4, no. 4, p. 1, 2022.

[14] S. M. Saragih and P. Sembiring, "Analisis perbandingan metode ARIMA dan double exponential smoothing dari Brown pada peramalan inflasi di Indonesia," *J. Fundam. Math. Appl.*, vol. 5, no. 2, pp. 176–191, 2022.
[15] N. A. Muzakir and M. Z. Yahya, "Analisis perbandingan model double exponential smoothing dan ARIMA untuk prediksi harga beras di Indonesia," *VARIANSI*, vol. 7, no. 1, pp. 7–20, 2025.
[16] J. Simanjuntak, "Analisis proksimat dan nilai kalor limbah sawit," *J. Mekanova*, 2024.
[17] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts, 2021.
[18] S. Suprianto, "Identifikasi hambatan pemanfaatan limbah cangkang dan serabut kelapa sawit sebagai bahan bakar biomassa," *J. Pedontropika*, vol. 9, no. 1, pp. 15–24, 2024.
[19] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," *Int. J. Forecast.*, vol. 22, no. 4, pp. 679–688, 2006.
[20] Z. Zahara, F. Fairus, and F. Muliani, "Aplikasi metode ARIMA dan metode DES dalam meramalkan jumlah kunjungan pasien rawat jalan poli umum," *AXIOM*, vol. 12, no. 2, pp. 139–152, 2023.
[21] R. J. Hyndman and Y. Khandakar, "Automatic time series forecasting: The forecast package for R," *J. Stat. Softw.*, vol. 27, no. 3, pp. 1–22, 2008.
[22] S. Yacob, M. A. Hassan, Y. Shirai, M. Wakisaka, and S. Subash, "Baseline study of methane emission from anaerobic ponds of palm oil mill effluent treatment," *Sci. Total Environ.*, vol. 366, no. 1, pp. 187–196, 2006.
[23] K. Braimakis, D. Magiri-Skouloudi, D. Grimekis, and S. Karellas, "Energy-exergy analysis of ultra-supercritical biomass-fuelled steam power plants for industrial CHP, district heating and cooling," *Renew. Energy*, vol. 154, pp. 252–269, 2020.
[24] E. S. Gardner, "Exponential smoothing: The state of the art—Part II," *Int. J. Forecast.*, vol. 22, no. 4, pp. 637–666, 2006.
[25] F. Balci Torun, M. Kayakuş, O. Kabas, G. Moiceanu, and M.-G. Munteanu, "Food Production Index Forecasting for Sustainable Food Systems in Türkiye: A Machine Learning-Based Approach," *Foods*, vol. 15, no. 16, p. 2814, 2026, doi: 10.3390/foods15162814.
[26] J. C. Barrera Hernandez *et al.*, "Biomass-based energy potential from the oil palm agroindustry in Colombia: A path to low carbon energy transition," *J. Clean. Prod.*, vol. 449, p. 141808, 2024, doi: 10.1016/j.jclepro.2024.141808.
[27] N. Abdullah, F. Sulaiman, and H. Gerhauser, "Characterisation of oil palm biomass as feed for torrefaction process," *J. Oil Palm Res.*, vol. 27, no. 1, pp. 1–11, 2015.
[28] Y. L. Chiew and S. Shimada, "Current state and environmental impact assessment for utilizing oil palm empty fruit bunches for fuel, fiber and fertilizer—A case study of Malaysia," *Biomass and Bioenergy*, vol. 51, pp. 109–124, 2013.
[29] H. James, "Rancangan pabrik biogas terintegrasi ke pabrik kelapa sawit hasil proses tandan kosong kelapa sawit (TKKS) dengan kapasitas produksi 1170 ton/hari," Institut Teknologi Indonesia, 2023.
[30] A. D. Putra, D. Pratiwi, and M. Heryanto, "Studi potensi limbah biomassa kelapa sawit sebagai sumber energi listrik terbarukan," *J. ELKHA*, vol. 10, no. 2, pp. 45–53, 2018.
[31] E. J. Jamshidi *et al.*, "Predicting oil palm yield using a comprehensive agronomy dataset and 17 machine learning and deep learning models," *Ecol. Inform.*, vol. 81, p. 102595, 2024, doi: 10.1016/j.ecoinf.2024.102595.
[32] K. Laia, "Peramalan produksi crude palm oil (CPO) di Riau dengan metode ARIMA," Universitas Islam Riau, 2019.