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Utilization of the ARIMA Model for Predicting the Value of Coconut Export in Kalimantan Barat

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ABSTRACT

The manufactured coconut classified under HS code 08011100 is available in either shredded or dried form. In 2022, this variety of coconut is projected to account for 8.68% of the export value of manufactured coconuts in Indonesia. While Kalimantan Barat has not yet achieved the status of the largest coconut exporter in Indonesia, coconut remains the primary commodity in the plantation sub-sector and significantly contributes to the Regional Original Income (PAD) of Kalimantan Barat Province. Kalimantan Barat, with a potential coconut plantation area of 94,204 ha and a growing array of processed coconut products, stands poised to enhance the value of its coconut exports. This study seeks to examine prospective market conditions by predicting the export value of coconuts in shredded or dried form, serving as a foundational strategy for enhancing the value of coconut exports. The ARIMA (Autoregressive Integrated Moving Average) model is employed to forecast the value of coconut exports (HS 08011100) for the upcoming 4 periods. During the process of identifying the best model, the ARIMA model (2,1,1) was selected, yielding a MAPE value of 26.63%. This indicates that the forecasts for coconut export values (HS 08011100) remain acceptable. The estimated coconut export value serves as a valuable planning reference for stakeholders aiming to enhance future coconut exports.

Keywords: Coconut, Export, ARIMA

INTRODUCTION

A significant export value is associated with the commodity known as coconut, which is exported from Indonesia. From 2013 to 2022, the value of coconut exports in Indonesia has expanded at an average annual growth rate of 13.35% (Pusdatin Agriculture, 2023). This growth has occurred during the course of the period. In addition, Pusdatin Agriculture (2023) states that Indonesia ranks first as an exporter of coconuts in shell with a contribution of 56.68% to the total world export volume and ranks second after the Philippines in the world exporter of desiccated coconut. An example of a manufactured coconut that falls under the HS code 08011100 is one of the many types of coconut goods that are available for purchase in Indonesia. Shredded or dried coconut is a form of coconut that falls under the HS 08011100 category. The value of manufactured coconut exports from Indonesia is expected to contribute 8.68% of the total value in 2022, according to Pusdatin Agriculture (2023). Over the course of the year from January to September 2023, the value of manufactured coconut exports (HS 08011100) fell from USD 55,018 million to USD 53,875 million. All of Indonesia's provinces are responsible for producing coconuts, which is the primary factor that determines the contribution of coconut exports to Indonesia. Coconut production centres are dispersed across several provinces in Indonesia, according to the Agricultural Data and Data Centre (2023). Furthermore, based on the average coconut production per province for five years, specifically from 2018 to 2022, the ten central provinces are responsible for producing 66.34% of the total contribution of coconut production in Indonesia. Riau, Sulawesi Utara, Jawa Timur, Maluku Utara, Sulawesi Tengah, Jawa Tengah, Jambi, Maluku, Sumatera Utara, and Jawa

Barat are some of the provinces that are also involved in the production of coconuts. Kalimantan Barat Province, on the opposing side, is responsible for 2.9 percent of the total coconut output in Indonesia. As a result, the exportation of coconuts from this region also makes a little contribution to the overall exportation of coconuts inside Indonesia.

Coconut is one of the most important commodities in the plantation sub-sector (BPS Kalbar, 2023) and one of the most significant contributors to PAD/Pendapatan Asli Daerah (Regional Original Income) in Kalimantan Barat Province (Muliadiasti et al., 2024). This is despite the fact that Kalimantan Barat is not yet considered to be the province that exports the most coconut on the Indonesian market. In 2023, the area of coconut plantations in Kalimantan Barat reached 94,204 hectares, which is equivalent to 0.64 percent of the total land area of Kalimantan Barat (BPS Kalimantan Barat, 2024). This provides support for the stated statement. The use of processed items made from coconut is growing (Oktari et al., 2023); thus, there is a chance to raise the export value of coconut, particularly shredded or dried coconut. This is a significant opportunity.

Kalimantan Barat is confronted with many obstacles when it comes to the chances to boost coconut exports. These challenges include a drop in productivity (Kalimantan Barat Provincial Plantation and Livestock Service, 2024) and a quality of coconut that does not meet the standards of nations that export coconuts (Pusdatin Agriculture, 2023). Therefore, there is a need for various parties to make efforts and develop strategies in order to raise the value of coconut exports, particularly those that are shredded or dried. In the first step of the process, it is possible to examine the conditions of the market in the future by making a prediction regarding the value of coconut exports. For the purpose of forecasting the value of coconut exports, there are a variety of time series methods that can be utilized, one of which is the ARIMA model. According to Rezaldi et al. (2021), the ARIMA model is more suitable for use in short-term forecasting because it makes use of previous data that is already available in its application.

This research uses the ARIMA (Autoregressive Integrated Moving Average) model as a forecasting method. This selection is based on the results of previous studies which show that the ARIMA model is effective in predicting data with similar characteristics, namely the value of exports even with different commodities. In research conducted by Hesty et al. (2023), which applied the ARIMA method in forecasting the export value of rubber commodities in Kalimantan Barat with the best model, namely ARIMA (1,1,0) and had a MAPE value of 20.7% which showed that the forecasting accuracy was acceptable. Ruliana et al. (2023) have compared forecasting methods, namely the ARIMA and Single Exponential Smoothing methods in forecasting the export value of cocoa commodities in Indonesia with the result that the ARIMA method is the best method in forecasting with the ARIMA (1,0,1) model and a MAPE value of 10.38060%. Then, research by Robbani et al. (2023) also applied the same method as this study, namely the ARIMA method in forecasting the value of Indonesian exports in June 2023 using MAPE as a measure of forecasting accuracy.

The ARIMA model will be utilized in this study to estimate the value of coconut exports (HS 08011100) over the subsequent four time periods. In previous research by Pusdatin Agriculture (2023), projections of coconut production and availability for domestic consumption in Indonesia from 2023 to 2027 were carried out with ARIMA and Transfer Function models with the result that it will experience a decline over the next five years. This research has novelty because until now no previous research has been found that specifically forecasts the export value of shredded or dried coconut commodities (HS 08011100) in Kalimantan Barat with the ARIMA model. In addition, the data that was utilized is the most recent historical data for the commodity known as shredded or dried coconut (HS 08011100), namely beginning in January 2019 and continuing through August 2024. Monthly, this information is gathered from the Directorate General of Customs and Excise (DJBC), which is part of the Ministry of Finance. It is based on reports from the PEB documents, which are presented in the form of HS-8 digit code groups by the PEB. It is hoped that by providing an estimate of the export value of shredded and dried coconut based on the results of the forecast, it will be able to assist stakeholders such as farmers, exporters, and the government in planning production and marketing to increase the competitiveness and sustainability of shredded or dried coconut exports from Kalimantan Barat in the months and years to come.

METHODOLOGY

A monthly analysis of the value of coconut exports (HS 08011100) in Kalimantan Barat is the topic of this research, which makes use of data that originates from the Directorate General of Customs and Excise (DJBC), which is part of the Ministry of Finance. There are 68 samples that were used for the data collection, which were collected between January 2019 and August 2024. The Autoregressive Integrated Moving Average (ARIMA) Model will be utilized to do a forecasting study on these data.

Table 1. Coconut Export Value Data (HS 08011100) from January 2019 to August 2024

Month	**Coconut Export Value (USD)**					
	2019	**2020**	**2021**	**2022**	**2023**	**2024**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
January	396,042	222,438.12	1,372,994.63	251,968.988	522,296.16	335,718.15
February	300,016	650,222.5	338,846.42	225,364.961	327,018.36	765,169.56
March	309,909	505,703.5	748,096.49	495,593.21	530,348.874	475,888.313
April	441,763	771,159.2	924,327.6	247,154.1	251,113.983	590,635.427
May	184,826	781,523.15	369,138.496	499,744.75	605,560.104	679,943.88
June	318,379	1,090,090.1	1,085,825.82	509,738.464	641,650.654	617,361.206
July	283,338	1,454,202.8	489,832.65	51,821.116	257,547.799	890,330.712
August	123,400	1,045,244.4	273,107.03	177,282.56	674,752.197	874,923.195
September	358,458	1,056,288.9	706,439.46	591,923.837	594,203.484	
October	693,717	973,454.62	445,837.6	298,007.912	439,420.017	
November	125,198	371,883.35	134,696.05	451,976.317	544,434.502	
December	424,775	539,329	263,949.53	639,929.119	537,593.122	

Source: Ministry of Finance, Directorate General of Customs and Excise (DJBC) (2024)

The research data that is used in time series analysis is divided into two distinct parts: the training data and the testing data. Data from January 2019 to March 2024 make up the training data, which consists of 63 samples. The testing data, on the other hand, is comprised of 5 samples, which are data from April 2024 to August 2024. During the process of developing the ARIMA model, the training data is utilized as experimental data, whilst the testing data is utilized as a tool to evaluate the accuracy of the ARIMA model when it comes to forecasting.

ARIMA Model

An Autoregressive Integrated Moving Average Model known as ARIMA was investigated by George Box and Gwilym Jenkins in 1976 (Quang et al., 2024). Additionally, the ARIMA Box-Jenkins model is a common name for this particular model. For the purpose of producing accurate short-term projections, the ARIMA model is utilized in time series analysis, forecasting, and control. This model makes use of both historical data and current values (Ruliana et al., 2023).

The Autoregressive (AR) and Moving Average (MA) components of the ARIMA model require the data to be steady (Integrated). The ARIMA model is a combination of the two. A process with linear dependency of lag values and random errors is referred to as the autoregressive model of order p ($AR(p)$). The following is an example of how this process is mathematically expressed.

$$\phi_p(B)Y_t = e_t$$

where

$$\phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)$$

According to the following equation, the moving average model of order q ($MA(q)$). is a process that is characterized by means of a weighted linear equation of random error and its lag value.

$$Y_t = \theta_p(B)e_t$$

where

$$\theta_p(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$$

A non-stationary time series model is used to depict the ARIMA model. This model is denoted as ARIMA (p, d, q), which stands for the Autoregressive, Differentiating, and Moving Average process orders in sequential order (D. & Syukri, 2020). According to Sari et al. (2024), a process Y_t is considered to operate according to the ARIMA model, which is considered to be non-stationary on average when there is an order d ($d \geq$ 1). The following is an example of how this model might be written (Aprilianti et al.,).

$$\phi_p(B)(1 - B)^d Y_t = \mu + \theta_q(B)e_t$$

where :

Y_t : actual data at time t

d : differencing of order-d

ϕ_p : parameters of the p-th order autoregressive model

θ_q : parameters of the q-th order moving average model

B : Backshift operator

e_t : error at time t

There are a number of processes that need to be completed in order to conduct out ARIMA model analysis (p, d, q). These stages include identifying the model, estimating the parameters, performing diagnostic testing, choosing the most appropriate model, and forecasting. In the ARIMA model, the stationarity of the data will first be checked. If the data is not stationary in the mean (as determined by the ADF (Augmented Dickey-Fuller) test), it will be overcome by a differencing process. If the data is not stationary in the variance, it will be overcome by a transformation process. After that, the process of determining the temporary model will be carried out by utilizing ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots (Ferdy & Putra, 2020). Following that, the parameters of the model are estimated, and the residual diagnostic test, which is the difference between the results of the estimation and the historical data, is carried out until the residuals are mutually independent and have a normal distribution (Pratiwi et al., 2023). The following step is to choose the model that is the most suitable. Subsequently have obtained the best model (which can be seen based on the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), etc. with the least values, it is able to move on to the next stage, which is the forecasting stage.

RESULTS AND DISCUSSION

This study makes use of data pertaining to the value of coconut exports (HS 08011100) for 68 samples that were gathered during the months of January 2019 and August 2024. With the assistance of the RStudio software, this data will be transformed into a time series model by employing the

ARIMA statistical model approach. The stages of the ARIMA model analysis will be discussed in more detail below.

Model Identification

In the first step of the process, a plot of data on the value of coconut exports (HS 08011100) will be created. The purpose of this graph is to see the variations in the value of coconut exports over the course of time. The value of coconut exports (HS 08011100) in Kalimantan Barat is plotted in Figure 1 that spans the years 2019 through 2024.

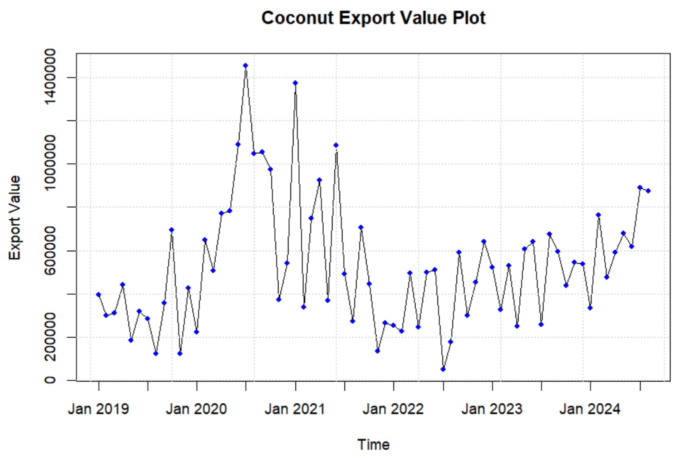


Figure 1. Time series plot of coconut export value
Source: Processed from Ministry of Finance, Directorate General of Customs and Excise (DJBC), 2024

Figure 1 illustrates that the value of coconut exports (HS 08011100) in Kalimantan Barat is subject to fluctuations on a regular basis. Within this time frame, the maximum value of coconut exports happened in July 2020, totaling to 1,454,202.79 USD. After that, the value of coconut exports continued to decrease until July 2022, and then gradually increased until August 2024.

In addition to that, a training data graph in the form of an ARIMA time series model will be developed based on the value of coconut exports. This graph will be utilized to generate the model. There are 63 samples, and Figure 2 is a training data plot that shows the values of coconut exports.

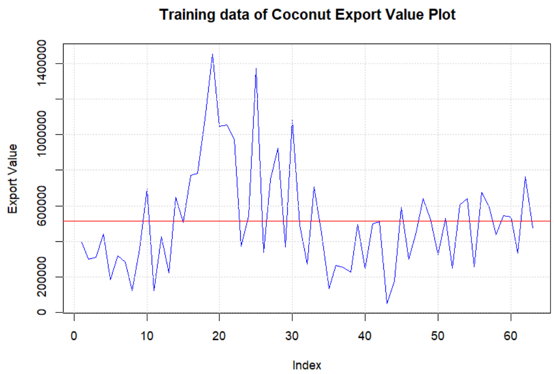


Figure 2. Time series plot of training data on coconut export values
Source: Processed from Ministry of Finance, Directorate General of Customs and Excise (DJBC), 2024

Based on Figure 2, it is possible to observe that the value of coconut exports during this time period does not follow the average value (the red line), and it is also possible to assert that the time series data is not stationary in terms of the average. Therefore, the first thing that we will do is use the

Box-Cox plot, which can be found below in Figure 3, to determine whether or not the data in variance are stationary.

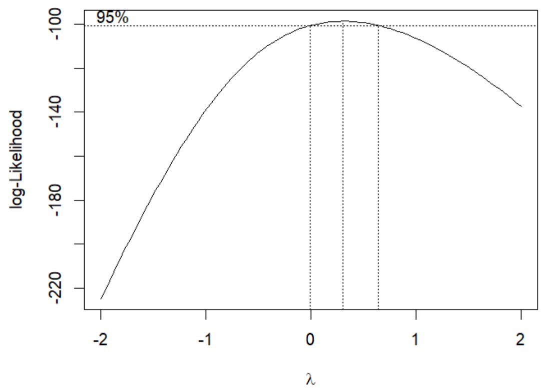


Figure 3. Box-cox test results
Source: Processed from Ministry of Finance, Directorate General of Customs and Excise (DJBC), 2024

Because $\lambda \neq 1$ ($\lambda = 0.3030$) is visible on the Box-Cox plot, it is possible to draw the conclusion that the data is not stationary in terms of variance. This conclusion is based on Figure 3. In order to get around this obstacle, a Box-Cox transformation will be performed in order to attain stationarity in the variance. Figure 4 below displays the outcomes of the Box-Cox test that was performed on the data after it was converted.

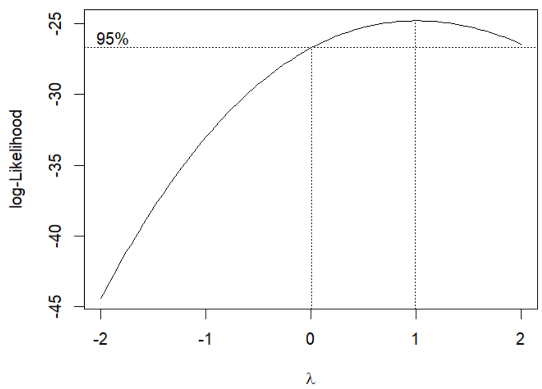


Figure 4. Box-Cox test results
Source: Processed from Ministry of Finance, Directorate General of Customs and Excise (DJBC), 2024

Based on the information presented in Figure 4, it is evident that the lambda value is extremely close to 1 ($\lambda = 0.9898$), which indicates that the data is stationary in variance following the transformation operation. Using the data that was obtained via the Box-Cox transformation, we proceed to test stationarity in the mean using the ADF (Augmented Dickey-Fuller) test. This is done after the assumption of stationarity in the variance has been satisfied. The results of the ADF test from the training data, which is stationary in the variance and is referred to as data_var, are presented in Table 2.

Table 2. ADF test results

Data	ADF Statistic	P-value	Description
(1)	(2)	(3)	(4)
data_var	-2.1812	0.5015	Non Stationary

Source: Processed from ARIMA model (2024)

The conclusion that the data is not stationary in terms of the average may be drawn from the data shown in Table 2, which can be found above. A differencing procedure was carried out in order to get around the fact that the p-value is more significant than 0.05, as can be seen from the table. Data_diff is the name given to the training data that has been differencing, which is presented in Table 3.

Tabel 3. ADF test results after differencing

Data	ADF Statistic	P-value	Description
(1)	(2)	(3)	(4)
data_diff	-4.7325	0.01	Stationary

Source: Processed from ARIMA model (2024)

The p-value acquired from the ADF test findings presented earlier is lower than the significance level of 0.05, which means that it is possible to assert that the data is stationary in the mean. It was determined after the differencing process was carried out. Therefore, the training data fulfill the assumption of data stationarity in terms of both the variance and the mean. After differencing, the training data are plotted in Figure 5, which can be found here.

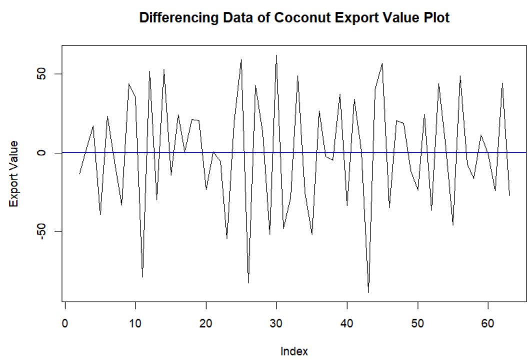
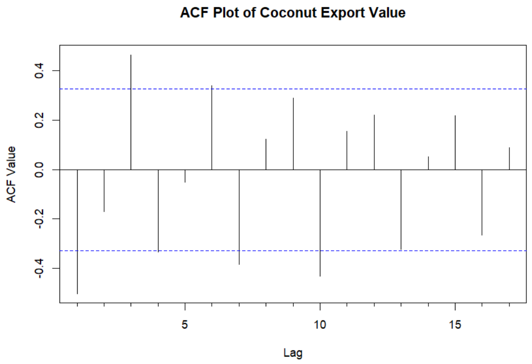


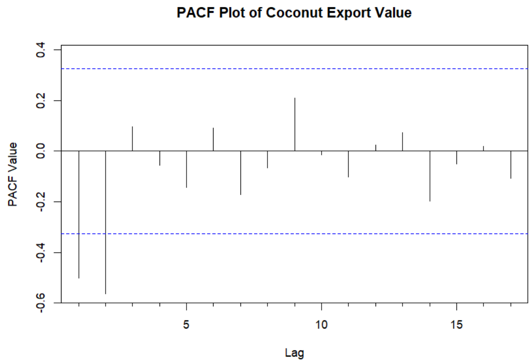
Figure 5. Training data of coconut export value after differencing plot

Source: Processed from ARIMA model, 2024

Through the use of the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots, the ARIMA model order was then identified by utilizing the differencing data.



(a)



(b)

Figure 6. Plot: (a) ACF and (b) PACF
Source: Processed from ARIMA model, 2024

According to Figure 6, it is possible to observe that the ACF plot experiences a cutoff (ACF value out of the significant line) at the first, third, fourth, sixth, seventh and tenth lags so that it can be determined that the order q is 1, 3, 4, 6, 7 and 10. On the other hand, the PACF plot experiences a cutoff (PACF value out of the significant line) at the first and second lags so that it can be determined that the order p is 1 and 2. A temporary model simpler is selected by using the ACF and PACF plots as a basis for forecasting using the ARIMA model, namely the ARIMA (2,1,1), ARIMA (2,1,0), and ARIMA (0,1,1) models.

Parameter Estimation

After obtaining the temporary model, which corresponds to the ARIMA (2,1,1), ARIMA (2,1,0), and ARIMA (0,1,1) models, the next step is to estimate the model's parameters. The data utilized in estimating the temporary model's parameters is data_var. Table 4 reveals the results of the parameter estimation performed on the temporary model.

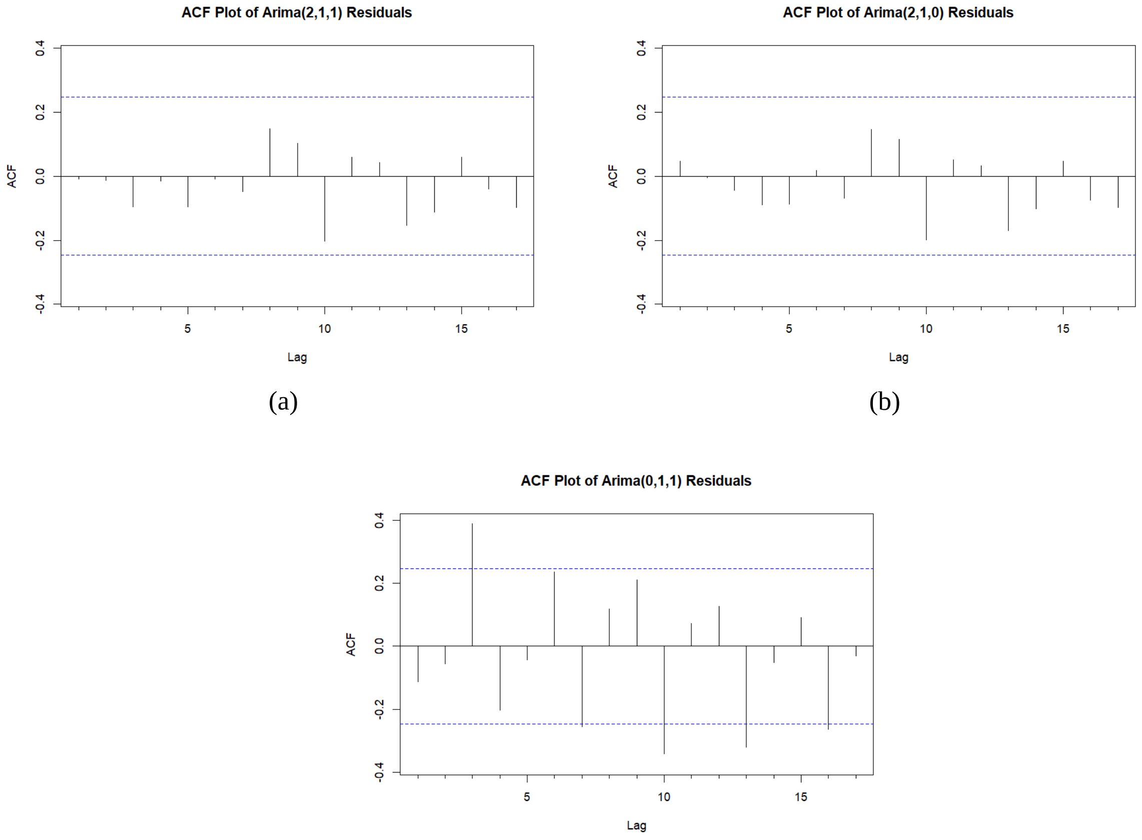
Table 4. Parameter estimation results

Model	**Parameter**	**Value**
(1)	**(2)**	**(3)**
ARIMA (2,1,1)	ϕ_1	-0.9034
	ϕ_2	-0.6195
	θ_1	0.1877
ARIMA (2,1,0)	ϕ_1	-0.7768
	ϕ_2	-0.5556
ARIMA (0,1,1)	θ_1	-0.6999

Source: Processed from ARIMA model (2024)

Diagnostic Checking

Diagnostic testing is the next step in the process. Tests for diagnosis can be broken down into two categories: the residual independence test and the residual normalcy test. Both tests are part of the diagnostic process. The residual independence test was carried out by examining the residual ACF plot of each model. In contrast, the Kolmogorov-Smirnov test was utilized to determine whether the residuals were normal. It is possible to make use of the model if both tests have been satisfied within the model. Figure 7 displays the outcomes of the residual ACF plot that the temporary model of the phenomenon generated.



(a) (b) (c)

Figure 7. ACF plot residual of: (a) ARIMA (2,1,1), (b) ARIMA (2,1,0), and (c) ARIMA (0,1,1)
Source: Processed from ARIMA model, 2024

Figure 7 demonstrates that the residual ACF values of the ARIMA (2,1,1) and ARIMA (2,1,0) models are within significant bounds. However, the ARIMA model (0,1,1) is precisely the reverse. It can be seen by comparing the two models. Both the ARIMA (2,1,1) and ARIMA (2,1,0) models can satisfy the independence assumption, as this can be deduced. Following that, the residual normality is evaluated using the Kolmogorov-Smirnov test, which can be found in Table 5.

Tabel 5. Kolmogorov-Smirnov test results

Residuals Model	**p-value**	**Description**
(1)	**(2)**	**(3)**
ARIMA (2,1,1)	0.9554	Normal
ARIMA (2,1,0)	0.9703	Normal
ARIMA (0,1,1)	0.8894	Normal

Source: Processed from ARIMA model (2024)

According to Table 5, it is evident that the p-value of all ARIMA models is greater than or equal to 0.05, indicating that the residuals are normally distributed. This conclusion is derived from the results of the Kolmogorov-Smirnov test. The ARIMA (2,1,1) and ARIMA (2,1,0) models were obtained as a result of the two tests that were carried out, and the model did not fail the diagnostic test. The process of picking the best model will continue once these models have been obtained.

Selection of the Best Model

The Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) will be the two measurement criteria used to determine which model is the most accurate. Table 6 is the forecasting results for the testing data period with ARIMA (2,1,1) and ARIMA (2,1,0).

Table 6. Forecasting results of testing data

Period	**ARIMA (2,1,1)**	**ARIMA (2,1,0)**
(1)	**(2)**	**(3)**
64	437,391.1	442,932.1
65	639,050.8	615,729.6
66	478,824.7	497,206.3
67	493,501.7	490,152.0
68	575,865.0	559.157.4

Source: Processed from ARIMA model (2024)

The accuracy of the ARIMA model in forecasting will be assessed by examining the error measures in the forecast results, namely the RMSE and MAPE values. The error value of the forecasting results utilizing the ARIMA model (2,1,1) and ARIMA model (2,1,0) are presented in Table 7.

Table 7. Accuracy of forecasting results

ARIMA Model	**RMSE**	**MAPE (%)**
(1)	**(2)**	**(3)**
ARIMA (2,1,1)	241,353.5	26.6304
ARIMA (2,1,0)	245,042.0	26.9904

Source: Processed from ARIMA model (2024)

According to Table 7, the ARIMA model (2,1,1) exhibits the lowest values for the assessment criteria RMSE and MAPE among the two ARIMA models. The optimal model selected is the ARIMA (2,1,1) model. The subsequent equation represents the ARIMA model (2,1,1):

$$Z_t = Z_{t-1} - 0.9034Z_{t-1} - 0.6195Z_{t-2} + 0.9034Z_{t-2} + 0.6195Z_{t-3} + 0.1877e_{t-1}$$

The forecasting data is returned to the original data scale using the following formula, which is necessary since the model is still in the Box-Cox transformation scale:

$$Z_t = \frac{Y_t^{\lambda} - 1}{\lambda} \rightarrow Y_t = (\lambda Z_t + 1)^{\frac{1}{\lambda}}$$

ARIMA (2,1,1)

Forecasting is the next stage to be completed. Because it fulfills the necessary assumptions, the ARIMA (2,1,1) model is deployed. The value of coconut exports (HS 08011100) will be forecasted for the next four periods, from September to December 2024. This forecasting will be carried out. Figure 8 plots actual data, estimated data, and forecast data for the next four periods using the ARIMA model

(2,1, 1). Table 9 displays the forecasted values for the value of coconut exports (HS 08011100) from September to December 2024.

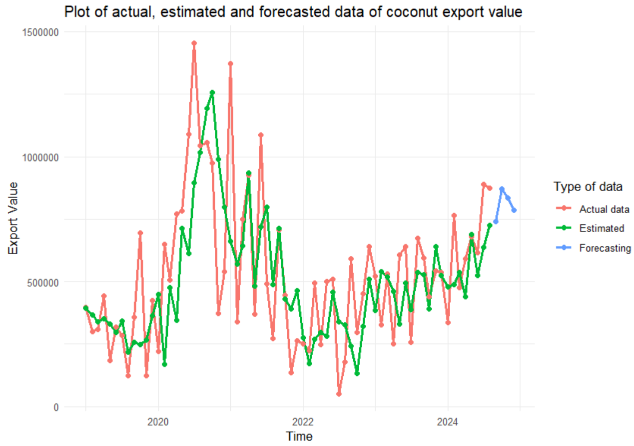


Figure 8. Plot of actual, estimated and forecasted data
Source: Processed from ARIMA model, 2024

Table 9. Forecasting results

Month (2024)	**Coconut Export Value (USD)**
(1)	**(2)**
September	741,335.4
October	871,352.6
November	833,486.3
December	786,682.0

Source: Processed from ARIMA model (2024)

In Kalimantan Barat, the value of coconut exports (HS 08011100) is calculated for the following four periods, which are September to December 2024, based on the findings of the forecasting made above. The ARIMA model (2,1,1) is used to calculate the value of coconut exports, and the error percentage of 26.63% (good forecasting results) continues to experience both increases and declines in the subsequent period. This can be seen in Figure 8 and Table 9, respectively.

Fluctuations in the value of coconut exports can be caused by several factors, including most smallholder farmers in Indonesia growing coconuts traditionally so that they are still unable to provide maximum economic value and market competition with other coconut-producing countries (Pusdatin Agriculture, 2023) and the unstable productivity and quality of coconuts produced in Kalimantan Barat (Kalimantan Barat Provincial Plantation and Livestock Service, 2024). Therefore, accurate forecasting results can help farmers, exporters and the government in planning production, improving quality and standardization, marketing strategies and collaboration with various parties so as to increase the competitiveness and sustainability of shredded or dried coconut exports from Kalimantan Barat in the international market.

CONCLUSIONS AND SUGGESTIONS

Two ARIMA models are suitable for use in predicting the value of coconut exports (HS 08011100) in Kalimantan Barat from January 2019 to August 2024, according to the findings of the analysis, which allows for the conclusion that two ARIMA models are suitable for use. The ARIMA

(2,1,1) model is the best since it has the lowest RMSE and MAPE values. The degree of AR (Autoregressive) measures two, the degree of differencing measures one, and the degree of MA (Moving Average) measures one.

Based on the findings of the forecasting, the estimated value of the export of shredded or dried coconut is approximately 741,335.4 USD in September 2024, approximately 871,352.6 USD in October 2024, approximately 833,486.3 USD in November 2024, and approximately 786,682.0 USD in December 2024. There are still fluctuations in the export value of shredded or dried coconut in Kalimantan Barat, as indicated by the results of these estimates. As a result, additional policies are required for stakeholders, including farmers, exporters, and the government, in order to plan production and marketing and increase the competitiveness and sustainability of coconut exports from Kalimantan Barat in the distant future.

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