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Prediction of Rice Harvest Yields Using the ARIMA Algorithm at the Agricultural Extension Center

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ABSTRACT

Rice production plays a crucial role in supporting regional food security; therefore, accurate forecasting is essential for effective agricultural planning. This study aims to forecast rice yields in Meurah Mulia District using a univariate Autoregressive Integrated Moving Average (ARIMA) model based on annual data from 2015 to 2024 obtained from the Agricultural Extension Agency. The modeling process includes stationarity testing using the Augmented Dickey–Fuller (ADF) test, model selection using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and residual diagnostics using the Ljung–Box test. The selected ARIMA model generates one-step-ahead forecasts for 2025 across 48 villages, with predicted yields ranging from 130.19 tons (Pri Ketapang) to 671.83 tons (Ulee Meuria), reflecting heterogeneous production patterns among villages. Model accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), with values below 2% across all villages,indicating satisfactory in-sample forecasting performance. However, this study applies a univariate ARIMA approach; therefore, external variables are not incorporated. The findings provide preliminary insights to support agricultural planning, while further research is recommended to enhance model robustness and generalizability.

I. INTRODUCTION

The agricultural sector plays a strategic role in supporting economic development and food security in Indonesia, particularly in rural areas such as Meurah Mulia District, North Aceh Regency, where the majority of the population depends on farming as their primary livelihood. Rice is one of the most important staple commodities in Indonesia, and fluctuations in rice production may significantly affect farmers' income as well as regional food stability. One of the main challenges faced by farmers in Meurah Mulia District is the uncertainty of rice harvest yields caused by various factors, including climate variability, pest and plant disease attacks, and limitations in resource management. These uncertainties highlight the need for a data-driven analytical approach to support more systematic and evidence-based decision-making in the agricultural sector [1]. The Agricultural Extension Center (Balai Penyuluhan Pertanian – BPP) of Meurah Mulia District plays a crucial role in assisting farmers and recording annual rice production data. However, the existing data management system remains largely administrative and has not been fully utilized for predictive analysis. As a result, planning decisions related to production targets, distribution strategies, and agricultural policies are often made without quantitative forecasting support. The application of time series analysis provides an opportunity to transform historical production records into meaningful predictive insights, thereby supporting more structured agricultural planning [2]. Among various time series forecasting techniques, the Autoregressive Integrated Moving Average (ARIMA) model is widely used for modeling and forecasting structured historical data. ARIMA is particularly suitable for short-term forecasting when the available dataset is limited and consists of regularly observed time intervals. Through stationarity testing and differencing processes, ARIMA can model underlying trends and temporal dependencies in time series data. Considering that this study utilizes annual rice production data from 2015–2024, ARIMA provides a statistically appropriate framework for analyzing production patterns within the observed period. The modeling process includes stationarity testing using the Augmented Dickey–Fuller (ADF) test, model identification based on ACF and PACF analysis, parameter selection using AIC and BIC criteria, and residual diagnostics to ensure model adequacy [3]. This study aims to apply the ARIMA model to forecast rice harvest yields in Meurah Mulia District based on historical production data obtained from the Agricultural Extension Center during the period 2015–2024. The research focuses on evaluating the forecasting performance of the ARIMA model within the observed dataset and interpreting production trends at the village level. It is important to note that this study applies a univariate modeling approach and does not incorporate external variables such as rainfall, planting area, or government intervention. Therefore, the forecasting results reflect historical production patterns rather than causal relationships. The findings are expected to provide preliminary quantitative insights to support agricultural planning and data-driven decision-making in Meurah Mulia District.

II. RESEARCH METHODOLOGY

A. *Place and Time of Research*

This research was conducted using rice production data obtained from the Agricultural Extension Center (Balai Penyuluhan Pertanian/BPP) of Meurah Mulia District, North Aceh Regency. The dataset used in this study consists of historical rice harvest data over a ten-year period, from 2015 to 2024, which includes information on rice varieties as well as the total annual rice production from forty-eight villages [2]. The data were subsequently processed and analyzed as the basis for developing a rice harvest yield forecasting model using the Autoregressive Integrated Moving Average (ARIMA) algorithm.

B. *Forecasting*

Forecasting is an analytical process carried out to estimate future values or events by utilizing historical data and the patterns derived from that data. This process involves the application of various approaches, both mathematical and algorithm-based, in order to produce estimates that can serve as a basis for decision-making. Through systematic data analysis, forecasting helps identify trends, fluctuations, and potential changes that may occur over time. In the context of planning, forecasting functions as an initial stage that aims to provide an overview of potential future conditions based on available information and identified patterns, thereby supporting more structured and informed planning activities. Although forecasting results are not absolute, this approach can be regarded as an educated estimate developed through specific methods to minimize uncertainty in the decision-making process and to reduce the risks associated with future-oriented policies and strategic actions [3].

C. *Research Procedure*

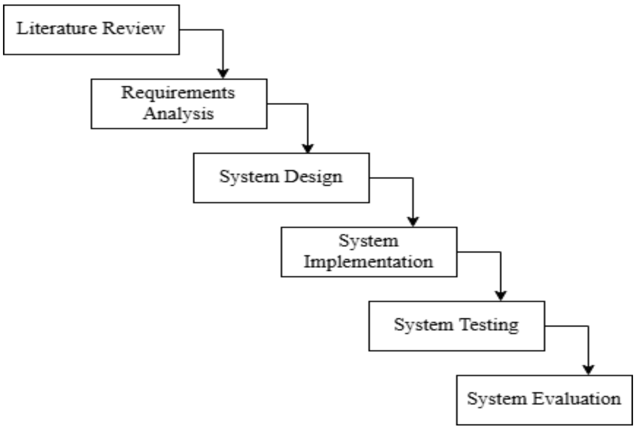


Figure 1. Research Procedure

This research was conducted through several systematically arranged stages to ensure that the development process of the prediction system was carried out in a well-organized and structured manner. The research stages implemented in this study include:

1. *Literature Review* : This stage involves reviewing various relevant references, such as books, scientific articles, and previous studies related to rice yield forecasting and the application of the ARIMA algorithm. The literature review aims to establish a strong theoretical foundation and to gain an understanding of the methods and approaches that have been applied in previous research [4].
2. *Requirements Analysis* : This stage is carried out to identify system requirements, both from the user perspective and from the functional aspects of the system. At this stage, the types of data to be used, the data processing requirements, and the expected system outputs are determined, ensuring that the developed system aligns with the objectives of the research.
3. *System Design* : At this stage, the system workflow, data structure, and interface design to be used are developed. This design process aims to provide a clear overview of the system processes prior to the implementation stage.
4. *System Implementation* : This stage represents the implementation of the system design into an operational system. At this stage, the ARIMA algorithm is implemented to process historical rice harvest data and generate predictions, and a web-based system is developed as a platform for presenting the forecasting results.

5. *Syistem Testing* : This stage is conducted to ensure that the developed system operates according to its intended functions. Testing is performed to examine the accuracy of the prediction results, the stability of the system, and the conformity of the outputs with user requirements.
6. *System Evaluation* : This stage aims to assess the overall performance of the system. The evaluation is conducted by analyzing the accuracy of the prediction results using error measurement methods and by assessing the usefulness of the system in supporting decision-making in the agricultural sector. The evaluation results serve as the basis for drawing conclusions and providing recommendations for future system development [5].

D. ARIMA Model Framework

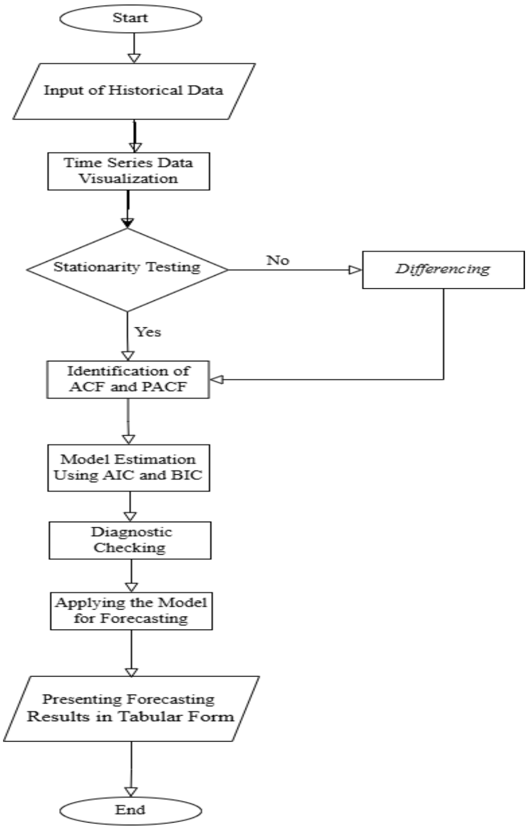


Figure 2. ARIMA Model

The rice harvest yield forecasting process using the Autoregressive Integrated Moving Average (ARIMA) algorithm is carried out through several interrelated stages that are systematically arranged. The process flow begins with the historical data input stage, which involves entering rice harvest yield data that have been collected from relevant data sources. This historical data serves as the primary basis for the analysis and forecasting process. The next stage is data visualization (data plotting), which aims to observe the general patterns of the data, such as trends, fluctuations, and possible seasonal indications. This visualization assists in understanding the characteristics of the data before further analysis is conducted. Subsequently, stationarity testing is performed to ensure that the data meet the requirements for ARIMA modeling. If the data are found to be non-stationary, a differencing process is applied until the data become stationary. Once the data are confirmed to be stationary, the next stage is model identification by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. This analysis is used to determine the appropriate ARIMA model parameters, namely the autoregressive order (p) and the moving average order (q), according to the data patterns. The following stage is model estimation, in which several ARIMA model combinations are tested and compared using model selection criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The model with the lowest AIC and BIC values is selected as the most optimal model. After the best model is obtained, diagnostic checking is conducted to evaluate the model's performance, including residual testing to ensure that the residuals are random and do not contain specific patterns. This stage is crucial to confirm that the constructed model satisfies the ARIMA assumptions. Finally, the validated ARIMA model is applied to perform forecasting of rice harvest yields for future periods. The resulting forecasts are then presented in tabular form to facilitate understanding and analysis by users. This stage marks the end of the forecasting process and indicates the completion of the entire sequence of analysis.

E. Definition of Rice

Rice (*Oryza sativa L.*) is a major cereal crop belonging to the Poaceae family and serves as a primary staple food for a large portion of the world's population, particularly in Asia, Africa, and South America [7]. In Indonesia, rice plays a crucial role in supporting national food security and economic stability. Therefore, maintaining stable rice production is essential, especially in agricultural regions. This study utilizes rice harvest data from 2015–2024 to analyze production trends, as presented in Table I for further analysis.

Table I (attached to the last page) presents annual rice production data collected from the Agricultural Extension Center (BPP) of Meurah Mulia District covering the period 2015–2024. The dataset consists of 10 annual observations per village. Given the limited number of time points, the analysis focuses on short-term forecasting using a univariate time series approach.

F. ARIMA

The Autoregressive Integrated Moving Average (ARIMA) method is one of the most widely used time series forecasting techniques for predicting future values based on patterns found in historical data. This method is effectively applied to data that exhibit stationarity, either inherently or after undergoing a differencing process to remove trends or seasonal patterns. ARIMA combines three main components, namely Autoregressive (AR), Integrated (I), and Moving Average (MA), enabling it to model time series data that are initially non-stationary [6]. The ARIMA approach is also known as the Box–Jenkins method, developed by George Box and Gwilym Jenkins through a systematic time series modeling framework. This method was introduced to address the limitations of traditional forecasting models that are less capable of handling non-stationary data. By integrating autoregressive and moving average components along with the differencing process, ARIMA has become a flexible method that is widely applied across various fields, including economics, meteorology, and systems engineering [7]. Mathematically, the ARIMA model is an extension of the Autoregressive Moving Average (ARMA) model. In this section, only the general form of the ARIMA equation is discussed, which can be expressed as follows:

$$X_t = \mu + (1 + \emptyset_1)X_{t-1} \ldots + \emptyset_p - \emptyset_{p-1}) X_{t-p} - \emptyset_p X_{t-p-1} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \ldots\ldots\ldots$$

Where :

e_t = error term at time t

X_t = time series data at time t

μ = constant value

$\emptyset_p$ = Autoregresive parameter of *p* = 1,2,3,...,*n*

θ_q = Moving Average parameter of *q* = 1,2,3,...,*n*

III. RESULT AND DISCUSSION

This stage presents the results of rice harvest yield forecasting obtained through the application of the Autoregressive Integrated Moving Average (ARIMA) method by utilizing historical harvest data sourced from the Agricultural Extension Center of Meurah Mulia District. The analysis is conducted to develop a forecasting model capable of representing changes in rice harvest yields over time based on the characteristics of the available data. The resulting forecasts provide an overview of future rice harvest yield trends for each area within Meurah Mulia District. The discussion focuses on the interpretation of the forecasting results and their relationship to historical data patterns, so that the findings can be used as a basis for consideration in agricultural planning and decision-making. In addition, the results of this study are expected to serve as an initial reference for further research related to the development of rice harvest yield forecasting methods [8].

A. ARIMA Model Identification

1. Data Stationarity

Stationarity testing is an essential step in time series analysis to evaluate whether rice harvest yield data remain statistically constant over time. A stationary series has a stable mean and variance, whereas non-stationary data typically exhibit trends or systematic changes across periods. Since the ARIMA model requires stationary data, it is necessary to verify this assumption before proceeding with model estimation. In this study, stationarity is assessed using the Augmented Dickey–Fuller (ADF) test. The ADF test is applied to examine whether a unit root is present in the series. If the p-value is greater than the significance level (α = 0.05), the data are considered non-stationary. Using rice production data from Meunye Payong Village for the period 2015–2024 as an example, the statistical results of the ADF test are summarized in Table III. These results are used to determine whether differencing is required before ARIMA modeling.

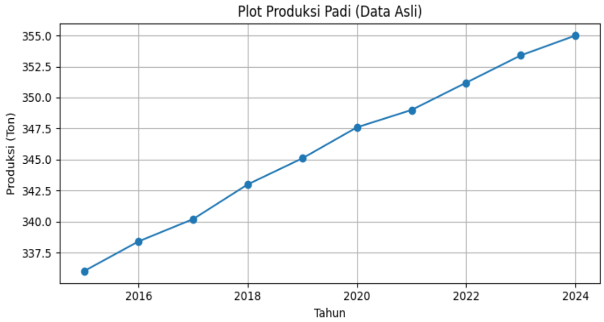


Figure 3. Non-stationary Data Plot

Figure 3 shows the plot of non-stationary data from Meunye Payong village. The next step will proceed with the first-order differencing (d=1). Mathematically, first-order differencing can be formulated as follows:

$$Y_t' = Y_t - Y_{t-1}$$

Where :

Y_t = production value at year-t

Y_{t-1} = production value in the previous year

Y_t' = result of first-order differencing

TABLE II
DIFFERENCING OF MEUNYE PAYONG VILLAGE

Village	Year	Harvest Yield	Yt'
Meunye Payong	2015	336	
Meunye Payong	2016	338,4	2,4
Meunye Payong	2017	340,2	1,8
Meunye Payong	2018	343	2,8
Meunye Payong	2019	345,1	2,1
Meunye Payong	2020	347,6	2,5
Meunye Payong	2021	349	1,4
Meunye Payong	2022	351,2	2,2
Meunye Payong	2023	353,4	2,2
Meunye Payong	2024	355	1,6

Table II presents the annual rice production data for Meunye Payong Village from 2015 to 2024. The “Harvest

Yield” column represents the original data, while “Yt'” shows the first-order differenced values calculated from consecutive yearly changes. The original series shows a consistent upward trend from 336 to 355 tons, indicating non-stationary behavior. After applying first differencing, the values fluctuate within a more stable range, suggesting that the trend component has been reduced before conducting the ADF stationarity test.

TABLE III
ADF STATISTIC

Test Condition	**ADF Statistic**	**p-value**	**Conclusion**
Original Data	-1,5943	0,4864	Not Stationary
First Difference	-3,9660	0,0016	Stationary

Based on Table III, the ADF test at the level produces a p-value of 0.4864, which is greater than 0.05. This indicates that the rice production data for Meunye Payong Village are not stationary at the level form, as the series exhibits an upward trend over time. Therefore, first-order differencing is applied to remove the trend component. After applying one differencing process, the ADF test yields a p-value of 0.0016, which is less than 0.05 [9]. This result indicates that the differenced series is stationary. Consequently, the order of integration (d) in the ARIMA model for Meunye Payong Village is determined to be 1.

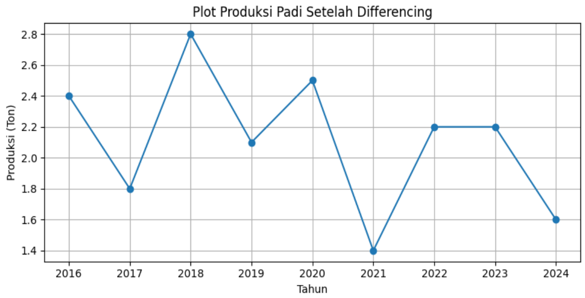


Figure 4. Plot of the Data after Differencing

Figure 4 presents the time series plot after first-order differencing for Meunye Payong Village. Unlike the original plot, which shows a clear upward trend, the differenced series fluctuates around a relatively constant mean without a systematic increase. The absence of a visible trend indicates that the data have become more stable. This visual pattern suggests that the differenced series is closer to stationarity before being confirmed by the ADF test.

2. *Model Identification Using ACF and PACF*

The model identification stage is conducted to determine the most appropriate ARIMA structure based on the characteristics of the time series data. At this stage, the analysis is carried out using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots derived from data that has already satisfied the stationarity property [10]. The patterns observed in the ACF and PACF plots serve as the basis for determining the orders of the autoregressive (p) and moving average (q) parameters in the ARIMA model. The data used in the model identification stage consist of rice harvest data from Meunye Payong Village for the period 2015–2024, which have undergone a first-order differencing process (d=1). The data have fulfilled the stationarity assumption, making them valid for use in the ARIMA model identification process for the subsequent analysis stage.

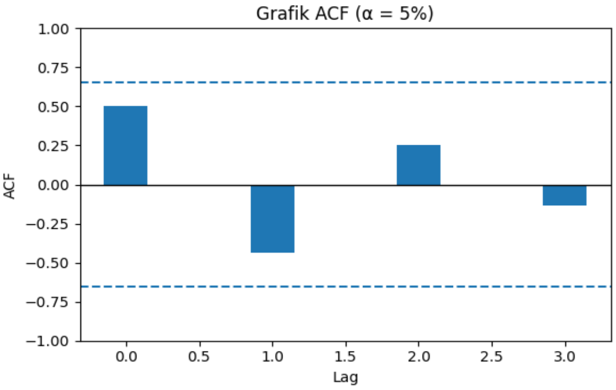


Figure 5. ACF Plot of Meunye Payong Village

Figure 4.3, the ACF plot, shows that the correlation bars do not cut off sharply at a specific lag, but rather decay gradually. All ACF values remain within the significance bounds at a 95 percent confidence level, indicated by the upper and limit lines on the plot. This pattern suggests that the data do not exhibit a pure moving average characteristic, but instead tend to contain an autoregressive component.

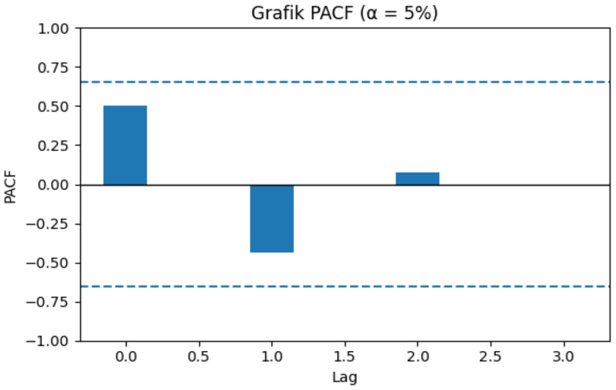


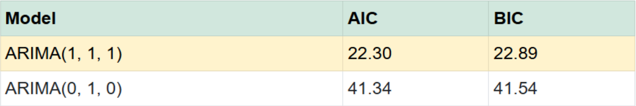
Figure 6. PACF Plot of Meunye Payong Village

The ACF plot provides an initial indication that the appropriate model is likely to involve an autoregressive component rather than a moving average. In Figure 4.4, the PACF plot shows that the correlation bars are significant only at lag 1, while the subsequent lags remain within the significance bounds and do not exhibit a strong pattern.

This pattern is known as a cut-off at lag 1, which is a characteristic of a first-order autoregressive process [11].

3. *Model Parameter Estimation*

The model identification stage was conducted using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the initial structure of the ARIMA model. Based on the analysis results, the rice production data from Meunye Payong Village satisfied the stationarity assumption after performing first-order differencing, so the differencing parameter ddd was set to 1. The PACF plot shows a clear cut-off at lag 1, while the ACF plot exhibits a gradual decay pattern, indicating the dominance of a first-order autoregressive component. Based on these patterns, the value of ppp was set to 1, while the value of qqq was considered at a low order, either 0 or 1. Therefore, the candidate models tested in the parameter estimation stage were ARIMA(1,1,0) and ARIMA(1,1,1).



Model	**AIC**	**BIC**
ARIMA(1, 1, 1)	22.30	22.89
ARIMA(0, 1, 0)	41.34	41.54

Figure 7. ARIMA Model Estimation

The figure presents a comparison of two ARIMA models, namely ARIMA(1,1,1) and ARIMA(0,1,0), based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values [12]. The evaluation results indicate that the ARIMA(1,1,1) model has lower AIC and BIC values compared to the alternative model, demonstrating a better balance between model fit and complexity. Therefore, the ARIMA(1,1,1) model was selected as the best model and was subsequently used in the residual diagnostic testing stage as well as for forecasting rice harvest yields [11].

4. *Diagnostic Checking*

After the best model was determined based on the AIC and BIC criteria, namely ARIMA(1,1,1), a thorough diagnostic test was carried out to ensure that the model met all fundamental assumptions required for time series analysis. This diagnostic examination primarily focused on the analysis of residuals, aiming to detect any remaining autocorrelation that might indicate a misfit of the model.

TABLE IV
LJUNG–BOX TEST

Differencing	**Residual**	**ACF Residual**	**Ljung-Box (Q)**
2,4	0,288889	-0,48512	4,651991
1,8	-0,31111	0,298364	
2,8	0,688889	-0,17067	
2,1	-0,01111		
2,5	0,388889		
1,4	-0,71111		
2,2	0,088889		
2,2	0,088889		
1,6	-0,51111		
2,111111			

Table IV presents the residual values obtained from the ARIMA(1,1,1) estimation, along with their corresponding autocorrelation (ACF residual) values and the Ljung–Box (Q) statistic. The residual column represents the difference between the observed differenced values and the fitted values generated by the model. Ideally, these residuals should fluctuate randomly around zero without forming any systematic pattern. The residual autocorrelation values shown in the table are relatively small and do not indicate persistent correlation across lags. Furthermore, the Ljung–Box test statistic (Q = 4.651991) does not show statistical significance at the chosen significance level, indicating that there is no remaining autocorrelation in the residuals. The residuals were subjected to the Ljung–Box test, which evaluates the randomness of the residuals up to a specified number of lags, providing a statistical measure to confirm whether the residuals behave as white noise [13]. The results of this test showed that the residuals did not display any significant autocorrelation and demonstrated a random pattern, confirming that they could be considered white noise. These findings, supported by the Ljung–Box statistics and residual analysis, indicate that the ARIMA(1,1,1) model satisfies the diagnostic requirements and can therefore be confidently used in the subsequent stage of the analysis, which involves forecasting future rice production yields [14].

5. *Arima Model Prediction*

The forecasting stage represents the final step in the time series analysis using the ARIMA method. This stage is carried out after the best model has been identified in Stage 3 and confirmed to be suitable through the diagnostic tests in Stage 4. The ARIMA(1,1,1) model, which has satisfied the stationarity assumption and whose residuals exhibit white noise behavior, is then used to predict rice production values for the upcoming periods in Meunye Payong Village [15]. The structure of the ARIMA(1,1,1) model can be described as follows :

$$\Delta Y_t = \emptyset_1 \Delta Y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Prediction Calculation :
Rice production for the year 2024 : $Y_{2024} = 335$
Last differencing value : $\Delta Y_{2024} = 1{,}6$
Last residual : $\varepsilon_{2024} = -0{,}511111$
AR(1) Parameter : $\emptyset_1 = 1{,}4$
MA(1) Parameter : $\theta_1 = 0{,}293$

Substitution of values into the model :
$\Delta Y_{2025} = (1{,}4 \times 1{,}6) + (0{,}293 \times 0{,}511111)$
$\Delta Y_{2025} = 2{,}24 + (-0{,}149)$

$\Delta Y_{2025} = 2{,}09$

Inverse *Differencing* (Final Predicted Value)
$\Delta Y_{2025} = \Delta Y_{2024} + \Delta Y_{2025}$
$\Delta Y_{2025} = 355 + 2{,}09$
$\Delta Y_{2025} = 357{,}09$

Based on the calculations using the ARIMA(1,1,1) model, the predicted change in rice production was obtained as 2.09. After performing the inverse differencing process, the forecasted rice production in Meunye Payong Village for the following period is 357.09. This result indicates an increase in rice production compared to the previous year, which is based on historical data patterns and past error components [16].

TABLE V
RICE HARVEST PREDICTION

No	Village Name	Year	Predicted Yield
1.	Rheng Bluek	2025	292.19
2.	Mesjid Bluek	2025	164.91
3.	Meuria Bluek	2025	239.63
4.	Reudeup	2025	393.64
5.	Dayah Bluek	2025	155.88
6.	Pulo Bluek	2025	380.11
7.	Mns Rangkileh	2025	214.00
8.	Ulee Ceubrek	2025	255.00
9.	Rayeuk Matang	2025	280.56
10.	Ulee Meuria	2025	671.83
11.	Manyang	2025	273.90
12.	Mns Tanjong	2025	260.68
13.	Kumbang	2025	482.15
14.	Pri Ketapang	2025	130.19
15.	Geulumpang	2025	312.80
16.	Blang Cut	2025	254.62
17.	Mns Mesjid	2025	385.83
18.	Tumpok Teungku	2025	265.29
19.	Rayeuk Paya Itek	2025	373.45
20.	Ubit Paya Itek	2025	341.42
21.	Meunasah Nga	2025	238.24
22.	Barat Paya Itek	2025	334.36
23.	Mns Keeh	2025	351.00
24.	Mns Mee	2025	607.56
25.	Menje Peut	2025	426.87
26.	Pulo Blang	2025	405.00
27.	Pulo Kitou	2025	348.83
28.	Teungoh Reuba	2025	334.41
29.	Ujong Reuba	2025	487.60
30.	Drien Puntong	2025	436.94
31.	Meunye Payong	2025	357.09
32.	Teungoh Kuta Batee	2025	432.80
33.	Pulo Drien Beukah	2025	396.11
34.	Ujong Kuta Batee	2025	420.53
35.	Nibong	2025	487.87
36.	Paya Bili	2025	298.59
37.	Baroh Kuta Batee	2025	392.83
38.	Gampong Teungoh	2025	532.60
39.	Beuringen	2025	623.90
40.	Ceubrek	2025	560.66
41.	Paya Kambuk	2025	444.19
42.	Blang Reuma	2025	560.18
43.	Ranto	2025	439.65
44.	Leubok Tuwe	2025	220.50
45.	Paya Sutra	2025	312.62
46.	Saramaba	2025	329.21
47.	Mns Baree Blang	2025	281.40
48.	Tualang	2025	291.53

Based on the modeling results, the forecasted rice production for 2025 across the 48 villages in Meurah Mulia Subdistrict exhibits considerable variation. These differences reflect heterogeneous production patterns derived from each village's historical time series data. Ulee Meuria is projected to have the highest production level (671.83 tons), followed by Beuringen and Mns Mee, whereas Pri Ketapang is expected to record the lowest forecast (130.19 tons). The variation in predicted values indicates structural differences in agricultural productivity among villages. Such disparities may be associated with differences in land area, farming practices, irrigation systems, and production capacity. These findings emphasize the importance of village-specific agricultural planning and resource allocation strategies.

B. *System Implementation*

The implementation of the rice harvest prediction system was carried out by developing a web-based application capable of automatically processing historical rice harvest data for each village. This system is designed to perform data analysis, select model parameters, and ultimately generate predicted harvest values for upcoming periods.

1. *Login Page*

The login page serves as the initial interface of the system, functioning as a security mechanism to control user access. On this page, users are required to enter a valid username and password to gain access to the system. This authentication process aims to restrict access rights according to user roles, ensuring that only authorized users can manage data and perform prediction processes. By implementing a login page, the system effectively safeguards the integrity and confidentiality of data. In addition, the system monitors user activities, such as data management, information entry, and the execution of rice harvest prediction processes [17]. The login page also helps minimize the risk of data misuse and unauthorized access to sensitive information. Furthermore, this mechanism contributes to accountability and traceability, as user actions within the system can be recorded and audited, enhancing overall system security and reliability.

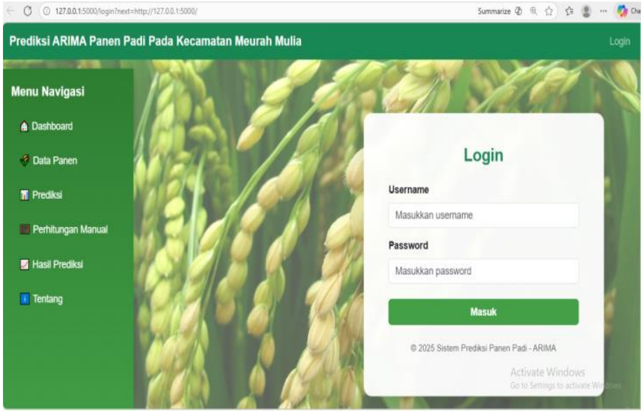
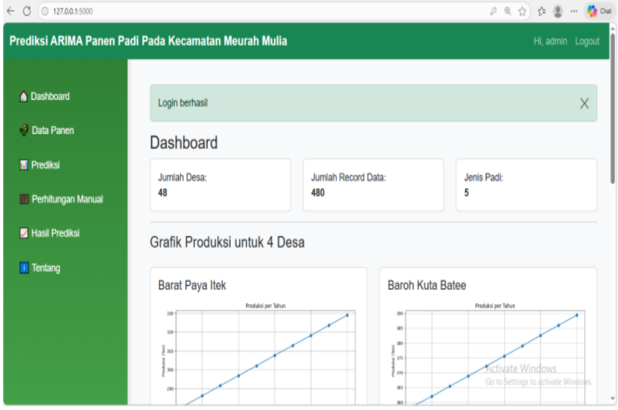


Figure 8. Login Page

2. *Dashboard Page*

The dashboard page presents a summary of the main information in the rice harvest prediction system, including the number of villages, total production data, and the types of rice used. In addition, production charts for several villages are displayed to provide an initial overview of historical data patterns. The dashboard serves as a quick information medium, offering users an immediate insight into the status and condition of the data within the system.



Login berhasil

Jumlah Desa: 48

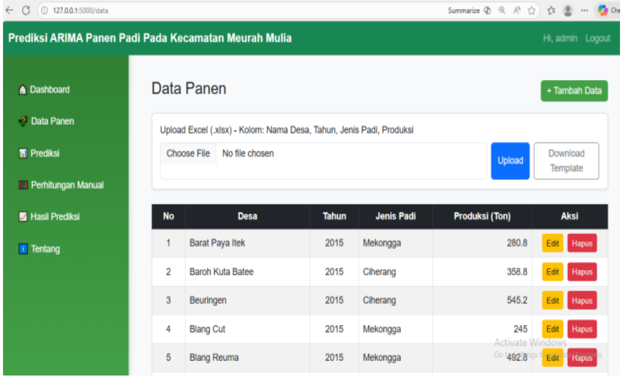
Jumlah Record Data: 480

Jenis Padi: 5

Figure 9. Dashboard Page

3. *Harvest Data Page*

The harvest data page is used to manage rice production data, which serves as the basis for the prediction process. On this page, users can add new data either by uploading Excel files or by entering the information directly into the system. The displayed data includes the village name, year, rice type, and production quantity (in tons). The harvest data table is presented in a structured format, containing information such as serial number, village name, production year, rice type, and production quantity in tons. Presenting the data in a table format facilitates users in monitoring, verifying, and conducting preliminary analyses of rice production data for each village. In the action column, edit and delete buttons are available, allowing users to update or remove data in case of errors or changes in information.



Upload Excel (.xlsx) - Kolom: Nama Desa, Tahun, Jenis Padi, Produksi

No file chosen

No	Desa	Tahun	Jenis Padi	Produksi (Ton)	Aksi
1	Barat Paya Itek	2015	Mekongga	280.8	Edit Hapus
2	Baroh Kuta Batee	2015	Ciherang	358.8	Edit Hapus
3	Beuringen	2015	Ciherang	545.2	Edit Hapus
4	Blang Cut	2015	Mekongga	245	Edit Hapus
5	Blang Reuma	2015	Mekongga	492.8	Edit Hapus

Figure 10. Harvest Data Page

4. *Prediction Page*

The prediction page represents the core component of the system, designed to forecast rice harvest yields using the Autoregressive Integrated Moving Average (ARIMA) method. On this page, users have the option to select the village for which predictions will be generated, based on the data available in the system's database. Once a village is selected, the system processes historical rice harvest data from previous years through time series analysis steps, including adjustments to the model parameters. The ARIMA parameters applied are displayed as part of the calculation process to ensure transparency and traceability of the analysis results. The resulting predictions are presented in a systematic and structured manner, allowing them to be used as supporting information for harvest planning and decision-making in the agricultural sector for upcoming periods.

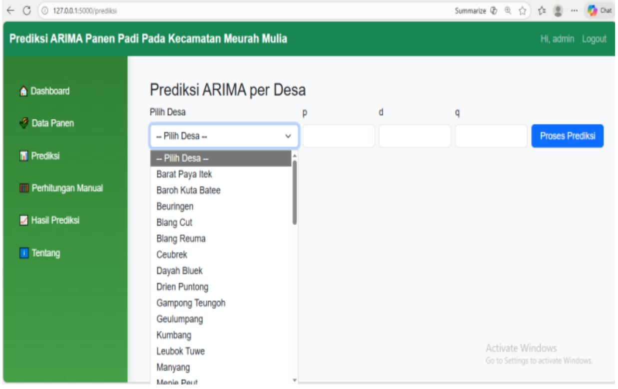
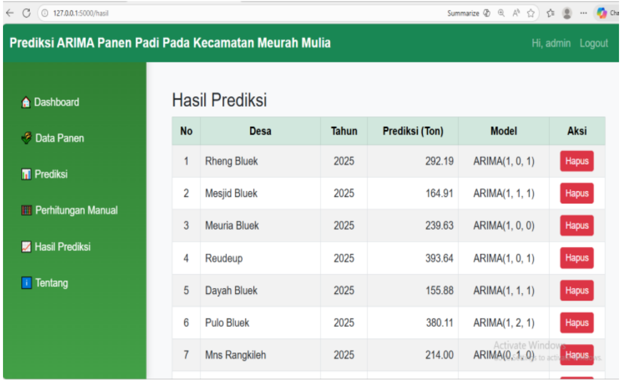


Figure 11. Prediction Page

5. *Prediction Result Page*

The Prediction Results page functions to display the forecasted rice harvest yields that have been processed using the ARIMA method. The information presented includes the village name, prediction year, predicted harvest values in tons, and the ARIMA model applied. This page facilitates the viewing, comparison, and management of predicted rice harvest results for each village in Meurah Mulia Subdistrict.



Hasil Prediksi

No	Desa	Tahun	Prediksi (Ton)	Model	Aksi
1	Rheng Bluek	2025	292.19	ARIMA(1, 0, 1)	Hapus
2	Mesjid Bluek	2025	164.91	ARIMA(1, 1, 1)	Hapus
3	Meuria Bluek	2025	239.63	ARIMA(1, 0, 0)	Hapus
4	Reudeup	2025	393.64	ARIMA(1, 0, 1)	Hapus
5	Dayah Bluek	2025	155.88	ARIMA(1, 1, 1)	Hapus
6	Pulo Bluek	2025	380.11	ARIMA(1, 2, 1)	Hapus
7	Mns Rangkileh	2025	214.00	ARIMA(0, 1, 0)	Hapus

Figure 12. Prediction Result Page

C. *ARIM Model Accurasy Using MAPE*

Mean Absolute Percentage Error (MAPE) is one of the methods used to measure the accuracy level of forecasted results. MAPE calculates the average absolute percentage error between actual values and predicted values. This method is widely used because its results are easily interpreted in percentage terms, making it convenient for evaluating the performance of the ARIMA model in predicting rice harvest yields. A smaller MAPE value indicates a higher accuracy level of the prediction model, whereas a larger MAPE value suggests that the forecasting results are less accurate [18].

TABLE VI
MAPE VALUE RANGE

Range MAPE	Definition
<10%	Excellent accuracy
10-20%	Good accuracy
20-50%	Moderate accuracy
>50%	Low accuracy

$$MAPE = \left(\frac{|Y_t - Y'_t|}{Y_t} \right) \times 100\%$$

Where :

Y_t = Actual Value

Y'_t = Predicted Value

MAPE Calculation

$$MAPE = \left(\frac{|355 - 357{,}09|}{335} \right) \times 100\%$$

$$MAPE = \left(\frac{|2{,}09|}{355} \right) \times 100\%$$

$$MAPE = 0{,}00589 \times 100\%$$

$$MAPE = 0{,}589\% \approx 0{,}59\%$$

TABLE VII
MAPE VALUE

No	Village Name	Year	Predicted Yield	MAPE Percentage
1.	Rheng Bluek	2025	292.19	0.55%
2.	Mesjid Bluek	2025	164.91	1.36%
3.	Meuria Bluek	2025	239.63	0.24%
4.	Reudeup	2025	393.64	0.34%
5.	Dayah Bluek	2025	155.88	0.31%
6.	Pulo Bluek	2025	380.11	1.09%
7.	Mns Rangkileh	2025	214.00	0.1%
8.	Ulee Ceubrek	2025	255.00	0.1%
9.	Rayeuk Matang	2025	280.56	0.2%
10.	Ulee Meuria	2025	671.83	0.14%
11.	Manyang	2025	273.90	0.1%
12.	Mns Tanjong	2025	260.68	0.26%
13.	Kumbang	2025	482.15	1.19%
14.	Pri Ketapang	2025	130.19	1.07%
15.	Geulumpang	2025	312.80	1.43%
16.	Blang Cut	2025	254.62	0.5%
17.	Mns Mesjid	2025	385.83	0.74%
18.	Tumpok Teungku	2025	265.29	0.72%
19.	Rayeuk Paya Itek	2025	373.45	0.66%
20.	Ubit Paya Itek	2025	341.42	0.75%
21.	Meunasah Nga	2025	238.24	1.06%
22.	Barat Paya Itek	2025	334.36	1.63%
23.	Mns Keeh	2025	351.00	0.1%
24.	Mns Mee	2025	607.56	0.32%
25.	Menje Peut	2025	426.87	1.03%
26.	Pulo Blang	2025	405.00	0.1%
27.	Pulo Kitou	2025	348.83	0.67%
28.	Teungoh Reuba	2025	334.41	0.42%
29.	Ujong Reuba	2025	487.60	0.97%
30.	Drien Puntong	2025	436.94	0.4%
31.	Meunye Payong	2025	357.09	0.59%
32.	Teungoh Kuta Batee	2025	432.80	0.37%
33.	Pulo Drien Beukah	2025	396.11	0.28%
34.	Ujong Kuta Batee	2025	420.53	0.17%
35.	Nibong	2025	487.87	0.97%
36.	Paya Bili	2025	298.59	0.47%
37.	Baroh Kuta Batee	2025	392.83	0.88%
38.	Gampong Teungoh	2025	532.60	0.1%
39.	Beuringen	2025	623.90	1.4%
40.	Ceubrek	2025	560.66	0.28%
41.	Paya Kambuk	2025	444.19	0.23%
42.	Blang Reuma	2025	560.18	1.37%
43.	Ranto	2025	439.65	0.44%
44.	Leubok Tuwe	2025	220.50	0.87%
45.	Paya Sutra	2025	312.62	1.47%
46.	Saramaba	2025	329.21	1.42%
47.	Mns Baree Blang	2025	281.40	0.1%
48.	Tualang	2025	291.53	0.25%

The MAPE results for each village illustrate the forecasting accuracy of the ARIMA model in predicting rice harvest yields. Although the MAPE values vary across villages, most fall within the categories of good to excellent accuracy. This indicates that the ARIMA model is generally capable of capturing the historical production patterns with a relatively high degree of precision. Overall, the model demonstrates satisfactory in-sample forecasting performance based on the MAPE evaluation. However, these accuracy values should be interpreted cautiously, as the evaluation is conducted using historical data without external validation or out-of-sample testing.

D. Study Limitations

Despite the satisfactory forecasting performance, this study has several limitations. First, the ARIMA model applied in this research is univariate and does not incorporate external variables such as rainfall, planting area, pest outbreaks, or government agricultural policies, which may influence rice production. Second, the dataset consists of annual observations, resulting in limited time-series depth. Finally, the findings are specific to Meurah Mulia District and may not be directly generalizable to other regions with different agricultural characteristics.

IV. CONCLUSION

This study demonstrates that ARIMA can model rice production trends in Meurah Mulia District with satisfactory accuracy within the observed dataset. The forecasting results indicate variations in production patterns among villages, reflecting differences in historical data characteristics. The findings provide preliminary insights that may assist local stakeholders in agricultural planning and resource allocation. However, the results should be interpreted within the scope of the available annual data. Future studies are recommended to incorporate relevant external variables and conduct comparative model evaluations to enhance forecasting robustness and generalizability.

REFERENCES

[1] Tasna Yunita, “Peramalan Jumlah Penggunaan Kuota Internet Menggunakan Metode Autoregressive Integrated Moving Average (ARIMA),” *J. Math. Theory Appl.*, vol. 1, no. 2, pp. 16–22, 2020, doi: 10.31605/jomta.v2i1.777.

[2] W. Fuadi, F. Fajriana, and R. M, “Peramalan Hasil Panen Padi Dengan Menggunakan Metode Double Exponential Smoothing Di Kecamatan Meurah Mulia,” *TECHSI - J. Tek. Inform.*, vol. 13, no. 1, p. 26, 2021, doi: 10.29103/techsi.v13i1.2772.

[3] M. Qamal, “Peramalan Penjualan Makanan Ringan Dengan Metode Single Exponential Smoothing,” *J. Penelit. Tek. Inform.*, vol. 8, no. 2, pp. 25–35, 2019.

[4] A. I. La Murdani and Y. W. A. Nanlohy, “Implementasi Model Autoregressive Integrated Moving Average (Arima) Untuk Peramalan Jumlah Penumpang Kapal Laut Di Pelabuhan Ambon,” *Var. J. Stat. Its Appl.*, vol. 3, no. 2, pp. 81–90, 2022, doi: 10.30598/variancevol3iss2page81-90.

[5] S. Safwandi, “Analisis Perancangan Sistem Informasi Sekolah Menengah Kejuruan 1 Gandapura Dengan Model Diagram Konteks Dan Data Flow Diagram,” *J. Teknol. Terap. Sains 4.0*, vol. 2, no. 2, p. 525, 2021, doi: 10.29103/tts.v2i2.4724.

[6] D. Benvenuto, M. Giovanetti, L. Vassallo, S. Angeletti, and M. Ciccozzi, “Data in brief Application of the ARIMA model on the COVID- 2019 epidemic dataset,” *Data Br.*, vol. 29, p. 105340, 2020, doi: 10.1016/j.dib.2020.105340.

[7] Y. F. Wijaya and A. Triayudi, “Penerapan Data Mining Pada Prediksi Harga Emas dengan Menggunakan Algoritma Regresi Linear Berganda dan ARIMA,” *J. Comput. Syst. Informatics*, vol. 5, no. 1, pp. 73–81, 2023, doi: 10.47065/josyc.v5i1.4615.

[8] R. H. Br Bangun, “Penerapan Autoregressive Integrated Moving Average (Arima) Pada Peramalan Produksi Kedelai Di Sumatera Utara,” *J. Agrica*, vol. 9, no. 2, p. 90, 2017, doi: 10.31289/agrica.v9i2.484.

[9] M. Terbaik, A. Integrated, and M. Average, “The Best Model of the Autoregressive Integrated Moving Average (ARIMA) Method for Predicting the Exchange Rate of the Indonesian Rupiah Against the US Dollar (USD) for the Period July 2025 - June 2026,” vol. 22, no. 2, pp. 427–435, 2026, doi: 10.20956/j.v22i2.48098.

[10] Y. Dong, S. Li, and X. Gong, “Time Series Analysis: An application of ARIMA model in stock price forecasting,” vol. 29, no. Iemss, pp. 703–710, 2017, doi: 10.2991/iemss-17.2017.140.

[11] Christina Purnama Yanti, Ni Komang Ita Cahyani, Theresia Hendrawati, Yuri Prima Fittryani, and Dewa Ayu Kadek Pramita, “Prediksi Harga Material Bangunan Dengan Autoregressive Integrated Moving Average (Arima) Pada CV. TJA,” *Tematik*, vol. 11, no. 1, pp. 47–55, 2024, doi: 10.38204/tematik.v11i1.1914.

[12] R. F. Syahrir, “Metode Autoregressive Integrated Moving Average (Arima),” *Academia.edu*, pp. 1275–1289, 2027.

[13] M. A. Hamjah, “Rice Production Forecasting in Bangladesh : An Application Of Box-Jenkins ARIMA Model,” vol. 4, no. 4, pp. 1–11, 2014.

[14] V. D. Sari and B. M. Sukojo, “Analisa Estimasi Produksi Padi Berdasarkan Fase Tumbuh Dan Model Peramalan Autoregressive Integrated Moving Average (Arima) Menggunakan Citra Satelit Landsat 8 (Studi Kasus: Kabupaten Bojonegoro),” *Geoid*, vol. 10, no. 2, p. 194, 2015, doi: 10.12962/j24423998.v10i2.828.

[15] Z. M. E. Atlam, A. Ewis, G. Dagnew, and A. Reda, “ARIMA models for predicting the end of COVID-19 pandemic and the risk of second rebound,” *Neural Comput. Appl.*, vol. 33, no. 7, pp. 2929–2948, 2021, doi: 10.1007/s00521-020-05434-0.

[16] H. Waryanto and D. A. Wanti, “Prediksi Penjualan Seragam Sekolah Dengan Menggunakan Metode Arima,” *J. Stat. dan Mat.*, vol. 1, no. 1, pp. 88–102, 2019.

[17] Z. Munirah, I. B. K. Widiartha, and S. I. Murpratiwi, “Sistem Peramalan Kelahiran, Kematian dan Kemiskinan berbasis Website dengan Metode Arima,” *Edumatic J. Pendidik. Inform.*, vol. 9, no. 1, pp. 1–10, 2024, doi: 10.29408/edumatic.v9i1.28423.

[18] A. D. Milniadi and N. O. Adiwijaya, “Analisis Perbandingan Model Arima Dan Lstm Dalam Peramalan Harga Penutupan Saham (Studi Kasus : 6 KRITERIA,” *Sibatik J.*, vol. 2, no. 6, pp. 1683–1692, 2023.

TABLE I
RICE HARVEST YIELD DATA

Village Name	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Rheng Bluek	254,8	259,3	263,7	268,9	272,4	276,8	280,5	283,5	287,1	290,6
Mesjid Bluek	144	144	146,2	148,5	150,9	153,2	155,6	158	160,3	162,7
Meuria Bluek	225,6	228,1	226,4	229,9	232	234,5	233	235,8	237,9	240,2
Reudeup	420	417	414	410	408	405	402	400	398	395
Dayah Bluek	155,1	154,8	155,4	155	155,6	155,2	155,7	155,3	155,9	155,4
Pulo Bluek	339	343	347	351	355	360	364	368	372	376
Mns Rangkileh	201,6	204	202,5	205,3	207	209,4	208,1	210,8	212,6	214
Ulee Ceubrek	240	243	241	245	247	249	248	251	253	255
Rayeuk Matang	280	279,4	280,1	279,7	280,3	279,8	280,4	279,9	280,5	280
Ulee Meuria	643,2	648	645,5	651,2	656	660,8	658,2	663,9	668,4	672,8
Manyang	259,7	262	260,8	263,5	265,2	267,6	266,1	269	271,4	273,9
Mns Tanjong	260	259,4	260,1	259,6	260,3	259,7	260,4	259,8	260,5	260
Kumbang	422,4	428,6	435,1	441,8	447,3	453,9	459,6	465,2	470,8	476,5
Pri Ketapang	122,2	125	123,4	127,1	126	128,8	127,3	130,1	129	131,6
Geulumpang	268,8	273	277,6	281,9	286,3	290,8	295,2	299,6	304	308,4
Blang Cut	245	248,1	246,4	250,2	248,8	252,6	250,9	254,1	252,8	255,9
Mns Mesjid	330	336,1	342,4	348,6	354,2	360,8	366,5	372,1	377,6	383
Tumpok Teungku	245	245	247,9	251,3	249,8	253,6	256,2	258,9	261	263,4
Rayeuk Paya Itek	375	372,8	374,2	371,9	373,5	371,2	372,9	370,6	372,1	371
Ubit Paya Itek	326,4	331	328,9	334,2	332,1	337,6	335,4	340,9	338,6	344
Meunasah Nga	230	233,6	231,9	235,4	233,8	237,1	235,6	239	237,5	240,8
Barat Paya Itek	280,8	286,1	291,5	296,8	302,1	307,6	312,9	318,2	323,6	329
Mns Keeh	338	340,5	337,8	342,2	345	343,6	346,8	349,1	347,9	351
Mns Mee	605	607,3	606,1	608,4	607	609,1	607,8	610	608,6	609,5
Menje Peut	387	390,2	393,5	397	401,2	405	409,3	413,8	418,1	422,5
Pulo Blang	390	392,5	388	394,2	398	396,4	399,8	403,1	401,6	405
Pulo Kitou	330	330	331,5	333	335,2	337	339,4	341,8	344	346,5
Teungoh Reuba	320	318,6	322,4	321	325,2	327	326,1	329,4	331,2	333
Ujong Reuba	440	444,8	449,2	454	459,1	464,5	469	473,6	478,2	482,9
Drien Puntong	422,4	418,9	416	419,2	423,6	426,4	428,1	431,5	433	435,2
Meunye Payong	336	338,4	340,2	343	345,1	347,6	349	351,2	353,4	355
Teungoh Kuta Batee	420	419,2	418,6	420,1	421,5	423,4	425	427,8	429,6	431,2
Pulo Drien Beukah	384	382,6	385,4	383,8	387	389,4	388,2	391	392,8	395
Ujong Kuta Batee	421,4	419,8	421	419,6	420,9	419,4	420,7	419,1	420,5	419,8
Nibong	441,6	446,2	450,8	455,4	460,2	465	469,6	474	478,8	483,2
Paya Bili	297,6	299,2	298,1	299,8	298,6	300,3	299	300,7	299,4	300
Baroh Kuta Batee	358,8	362	365,4	368,8	372,2	375,6	379	382,6	386	389,4
Gampong Teungoh	506	512,4	508,6	515,8	520,3	518,1	525,7	529,4	527,2	532,6
Beuringen	545,2	552,1	559,4	566,8	574,3	582,1	590	598,4	606,7	615,3
Ceubrek	537,8	532,4	539,6	544,2	540,1	546,8	551,2	548,7	554,3	559,1
Paya Kambuk	480	474,6	469,8	465,2	461	457,6	454,3	451,1	448	445,2
Blang Reuma	492,8	498,6	504,9	511,2	517,6	524,3	531,1	538	545,2	552,6
Ranto	432	427,6	424,2	428,8	433,4	431	435,7	439,2	437,1	441,6
Leubok Tuwe	202,4	204,1	205,8	207,6	209,3	211,1	213	214,8	216,7	218,6
Paya Sutra	272,8	276,2	279,8	283,5	287,3	291,2	295,2	299,4	303,7	308,1
Saramaba	288	291,6	295,3	299,2	303,1	307,2	311,4	315,7	320,1	324,6
Mns Baree Blang	266,6	269,8	267,4	271,1	274,6	272,3	276,8	279,2	277,6	281,4
Tualang	292,4	290,9	292,1	290,6	291,9	290,4	291,7	290,1	291,5	290,8
Ceubrek	537,8	532,4	539,6	544,2	540,1	546,8	551,2	548,7	554,3	559,1
Paya Kambuk	480	474,6	469,8	465,2	461	457,6	454,3	451,1	448	445,2
Blang Reuma	492,8	498,6	504,9	511,2	517,6	524,3	531,1	538	545,2	552,6
Ranto	432	427,6	424,2	428,8	433,4	431	435,7	439,2	437,1	441,6
Leubok Tuwe	202,4	204,1	205,8	207,6	209,3	211,1	213	214,8	216,7	218,6
Paya Sutra	272,8	276,2	279,8	283,5	287,3	291,2	295,2	299,4	303,7	308,1
Saramaba	288	291,6	295,3	299,2	303,1	307,2	311,4	315,7	320,1	324,6
Mns Baree Blang	266,6	269,8	267,4	271,1	274,6	272,3	276,8	279,2	277,6	281,4
Tualang	292,4	290,9	292,1	290,6	291,9	290,4	291,7	290,1	291,5	290,8

Source : Meurah Mulia District BPP