



## Time Series Seasonal Autoregressive Integrated Moving Average Model for Analysis of Rainfall Forecasting: Implementation on Agricultural Insurance

Agustini Tripena<sup>1\*</sup>, Zinedine Amalia Noor Mauludy Reihan<sup>2</sup>, Agung Prabowo<sup>3</sup>, Suroto<sup>4</sup>, Agus Sugandha<sup>5</sup>, Sukono<sup>6</sup>

<sup>1,2,3,4,5</sup>Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Jenderal Soedirman, Purwokerto, Indonesia.

<sup>6</sup>Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Jatinangor, Indonesia

Corresponding Author: [agustini.surbakti@unsoed.ac.id](mailto:agustini.surbakti@unsoed.ac.id)

### Abstract

*Cilacap is the largest regency located in the southwest of Central Java Province. The rain fall in Cilacap has seasonal variation for monthly period, thus information on rainfall is very important for the Government of Cilacap Regency its people, especially farmers. The usefulness of forecasting method in predicting the volume of rainfall is important. It motivates development of a system that can predict future amount of rainfall. A fluctuation analysis on forecasting result can be used for local government's policy making purpose. This paper analyses and presents SARIMA method to develop a forecasting model which may support and predict rainfall volume. The dataset for model development was collected from time series data published by Meteorology, Climatology and Geophysics Agency Tunggul Wulung Station from January 2009 to December 2022. The data were divided into data training (to December 2021) and data testing (January to December 2022) groups. The use of data training produced SARIMA model (2,0,2)(0,0,1)<sub>12</sub> as the selected model. The model achieved 0.70% for MAPE using data testing. It indicated the final model's capability to closely represent and made prediction based on the rainfall history dataset. The model produced was used to forecast the rainfall from January 2023 to December 2024. The forecast results were analyzed in relation to agricultural insurance program.*



**Keyword:** SARIMA, insurance, rainfall, risk, testing and training data.

## INTRODUCTION

Rainfall forecasting is important information for the government as reference to plan various activities in all governmental sectors, such as agriculture, fishery, plantation, etc. Seasonal ARIMA (SARIMA) is one method to make a time series forecasting model on various types of data such as data on rainfall (Aldrian, 2011), number of aircraft or railway passengers (Aswi, 2006), consumer price index (Wei, 2006), number of malaria cases (Arianto, 2010), need for energy and production of agricultural commodities such as rice, shallot, and corn (Brockwell, 1996); (Ervina, 2018); (Hatasuhut, 2014)).

Agricultural commodity production prediction is an important part of this research that such production depends on water availability that generally relies on rainfall (Lakitan, 2002). One types of agricultural insurance makes rainfall an object to be insured (Makridakis, 1983). This research focused on time series modeling for rainfall data using SARIMA method, associated with rainfall index based agricultural insurance.

Rainfall is an example of time series data since it is an observation from time to time with repetitions within a certain period. SARIMA method is one time series forecasting method using an iterative approach in identifying the most appropriate model out of the existing possible models. Research that uses SARIMA method tends to have relatively high forecasting accuracy for its detailed process and is deemed flexible that it follows the existing data pattern (Montgomery, 2008).

SARIMA method is used for data that are influenced by seasonal factors or there are repetitions of data pattern within a certain period ((Multiningsih, 2022); (Prabowo, 2019)). Permanasari (2001) produced SARIMA model (0,1,1)(1,1,1) (Prabowo, 2019) in forecasting the number of those infected by malaria based on the data issued by the Centers for Disease Control and Prevention (CDC) USA from January 1993 to December 2009.

The model obtained was evaluated in MAPE 21.6%. SARIMA method was used for forecasting Consumer Price Index in Sampit City by (Prabowo, 2020) with the best SARIMA model(1,1,0)(1,1,1) (Prabowo, 2019).

Multiningsih and Saleh (2010) obtained SARIMA model (4,1,0)(0,1,2) (Prabowo, 2020) for data on the number of passengers leaving Semayang Port with MAPE 14.05%. Meanwhile, the forecast of the number of passengers entering Semayang Port was SARIMA(0,1,1)(2,1,0)12 with MAPE 3.27%.

Meanwhile, (Wei, 2006) discussed prediction of shallot production in Nganjuk Regency

using SARIMA method, obtaining the best SARIMA model(3,0,2)(2,1,2)<sub>12</sub> with MAPE value 2.01%. MAPE values measure the level of forecasting accuracy on actual data, and quite low MAPE value was obtained below 10% out of the examples above.

Human needs water for daily life needs. Agriculture, plantation, animal husbandry and all types of human works need water. Excess of water is a problem and lack of water is also a problem. In general, water is derived from rainfall, thus rainfall forecasting is important (Prabowo, 2023). Cilacap is quite a large region and most of its people are farmers. Therefore, the author was interested in researching on the use of SARIMA method to create a rainfall forecasting model in Cilacap based on the rainfall data from 2009 to 2022, to be validated using published 2023 data. Further, based on the model obtained, rainfall forecasting was performed for the next five periods. Rainfall forecasting results are important related to rainfall index based agricultural insurance (Prabowo, 2023).

The Basic Theory section only discusses ARIMA model  $(p,d,q)$  and SARIMA model  $(p,d,q)(P,D,Q)^s$ . The other discussions in the Basic Theory section are on the examples of calculation of mean, variances, covariance, ACF function and PACF function of a given SARIMA model.

Time series variable is measured using a time series unit such as daily, monthly, quarterly, and annually. SARIMA model is a single (univariate) time series data forecasting model. SARIMA model only considers rainfall's dependency on past data without considering its dependence on other weather (element) variables such as temperature, air humidity, or wind speed. SARIMA model that considers the influence of such weather elements in rainfall forecasting is called multivariate time series model.

### ARIMA Forecasting Method

The general form of ARIMA  $(p,d,q)$  consists of three components ((Prabowo, 2023); Purnama, 2022); (Purwandari, 2019): differencing level  $d$ , autoregressive process order  $p$ , and moving average process order  $q$ . ARIMA  $(p,d,q)$  means a non-stationary time series that after a difference is taken from certain lag or differencing is performed becomes stationary. The time series contains AR model with order  $p$ , and MA model with order  $q$  (Purwandari, 2019). For example,  $d$ , is non-negative integer, then ARIMA model  $(p,d,q)$  can be stated by

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\varepsilon_t \quad (1)$$

where  $\varepsilon_t$  is white noise process,  $Z_t$  is discrete time variable for  $t=1,2,3,\dots$ ,  $\phi_p(B)$  is non-stationary autoregressive operator,  $\theta_q(B)$  is moving average operator, and  $B$  is backward shift

operator with  $B^k Z_t = Z_{t-k}$ .

In equation (1), define equations (2) and (3)

|                                                                        |     |
|------------------------------------------------------------------------|-----|
| $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)$         | (2) |
| $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)$ | (3) |

so, the ARIMA model is as follows

$$Z_t = \delta + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q}$$

where  $Z_t$  big variable of observation (occurrence) within time period  $t$ , constant is stated as  $\delta$ , random shock within time period  $t$  is  $\varepsilon_t$ , while  $\phi$  and  $\theta$  are consecutively autoregressive operator and moving average. Meanwhile, random shock  $\varepsilon_t$  is white noise (error) process within time period  $t$  that is assumed normally distributed and having mean 0 and variance  $\sigma_\varepsilon^2$ . In equation (2),  $\phi_1, \phi_2, \dots, \phi_p$  is AR coefficient in order  $p$ , and  $\theta_1, \theta_2, \dots, \theta_q$  is MA coefficient in order  $q$ .

### SARIMA Forecasting Method

SARIMA model is used when time series data show seasonal variation symptom. Notation for seasonal autoregressive is  $P$ , notation for seasonal moving average is  $Q$ , thus SARIMA  $(p, d, q)(P, D, Q)^s$  is obtained out of multiplicative process. Symbol  $s$  shows the length of seasonal period, for example  $s=7$  for daily and  $s=12$  for monthly data.

The formal form of SARIMA model is obtained through defining backshift operator  $B$ . Time series operation with backward  $k$  period is symbolized by  $B^k$  and defined by  $B^k y_t = y_{t-k}$ . Formally, backshift operator is used for stationary transformation. Time series process is called stationary if the statistical properties, which are mean and variance, are constant all the time. Stationary transformation is generally stated with equation (5)

|                                                             |     |
|-------------------------------------------------------------|-----|
| $Z_t = \nabla_s^D \nabla^d y_t = (1 - B^s)^D (1 - B)^d y_t$ | (5) |
|-------------------------------------------------------------|-----|

where  $Z$  is time series differencing,  $d$  is the order of non-seasonal differencing, and  $D$  the order of seasonal differencing. Further, the general form of SARIMA model  $(p, P, q, Q)$  is

|                                                                                |     |
|--------------------------------------------------------------------------------|-----|
| $\phi_p(B) \Phi_P(B^s) Z_t = \delta + \theta_q(B) \Theta_Q(B^s) \varepsilon_t$ | (6) |
|--------------------------------------------------------------------------------|-----|

SARIMA model in equation (4) has differencing order  $d=0$  and  $D=0$ . SARIMA model with non-seasonal and seasonal differencing orders is consecutively  $d$  and  $D$  constant  $\delta=0$  has form of equation (7).

|                                                                                             |     |
|---------------------------------------------------------------------------------------------|-----|
| $\Phi_P(B^s) \phi_p(B) (1 - B)^d (1 - B^s)^D Z_t = \theta_q(B) \Theta_Q(B^s) \varepsilon_t$ | (7) |
|---------------------------------------------------------------------------------------------|-----|

where  $\Phi_p(B^s)$  is seasonal autoregressive,  $\phi_p(B)$  is non-seasonal autoregressive,  $(1-B)^d$  is non-seasonal differencing,  $(1-B^s)^D$  is seasonal differencing,  $\theta_q(B)$  is non-seasonal moving average,  $\theta_q(B^s)$  is seasonal moving average, and  $\varepsilon_t$  is error

### Example of SARIMA Model

One example of stationary multiplicative SARIMA is SARIMA $^{(0,0,1)(0,0,1)^{12}}$ . Using equation (7) results  $Z_t = \theta_1(B)\Phi_1(B^{12})\varepsilon_t$ . Referring to equations (2) and (3), it results in equation

$$Z_t = (1 - \phi_1 B)(1 - \theta_1 B^{12})\varepsilon_t$$

$$Z_t = (1 - \phi_1 B - \theta_1 B^{12} + \phi_1 \theta_1 B^{13})\varepsilon_t$$

$$Z_t = (1 - \phi_1 B - \theta_1 B^{12} + \phi_1 \theta_1 B^{13})\varepsilon_t$$

$$Z_t = \varepsilon_t - \phi_1 B(\varepsilon_t) - \theta_1 B^{12}(\varepsilon_t) + \phi_1 \theta_1 B^{13}(\varepsilon_t)$$

$$Z_t = \varepsilon_t - \phi_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-12} + \phi_1 \theta_1 \varepsilon_{t-13}$$

Further mean, variance, auto-covariance, ACF value and PACF value will be calculated from process  $\{Z_t\}$ .

1. Mean of  $\{Z_t\}$  process is

$$E[Z_t] = E[\varepsilon_t - \phi_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-12} + \phi_1 \theta_1 \varepsilon_{t-13}] = 0$$

2. Variance of  $\{Z_t\}$  process is

$$\gamma_0 = \text{Var}(Z_t) = E[Z_t^2] - (E[Z_t])^2 = E[Z_t^2]$$

$$= E[(\varepsilon_t - \phi_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-12} + \phi_1 \theta_1 \varepsilon_{t-13})^2]$$

$$= E[(\varepsilon_t - \phi_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-12} + \phi_1 \theta_1 \varepsilon_{t-13})^2]$$

$$= (1 + \theta_1^2)(1 + \phi_1^2)\sigma_\varepsilon^2$$

3. Auto-covariance of  $\{Z_t\}$  process is

$$\gamma_1 = \text{Cov}(Z_t, Z_{t-1})$$

$$= E[(Z_t - E[Z_t])(Z_{t-1} - E[Z_{t-1}])]$$

$$= E[(Z_t Z_{t-1})]$$

$$\begin{aligned}
 &= E \left[ \begin{pmatrix} \varepsilon_t - \theta_1 \varepsilon_{t-1} - \Theta_1 \varepsilon_{t-12} + \theta_1 \Theta_1 \varepsilon_{t-13} \\ \varepsilon_{t-1} - \theta_1 \varepsilon_{t-2} + \Theta_1 \varepsilon_{t-13} \theta_1 \Theta_1 \varepsilon_{t-14} \end{pmatrix} \right] \\
 &= E \left[ -\theta_1 \varepsilon_{t-1}^2 - \theta_1 \Theta_1^2 \varepsilon_{t-13}^2 \right] \\
 &= -\theta_1 (1 + \Theta_1^2) \sigma_\varepsilon^2
 \end{aligned}$$

With the same method, it obtains  $\gamma_2 = \gamma_3 = \dots \gamma_{10} = 0$ . The value  $\gamma_{11}$  is calculated using the same way, obtaining  $\gamma_{11} = \theta_1 \Theta_1 \varepsilon_\sigma^2$ . Similarly, this applies to  $\gamma_{12} = -\theta_1 (1 + \theta_1^2) \sigma_\varepsilon^2$  and  $\gamma_{13} = \theta_1 \Theta_1 \varepsilon_\sigma^2$ .

The auto-covariance function of SARIMA model  $(0,0,1)(0,0,1)^{12}$  is written

$$\gamma_k = \begin{cases} (1 + \theta_1^2)(1 + \theta_1^2) \sigma_\varepsilon^2 & , k = 0 \\ -\theta_1 (1 + \theta_1^2) \sigma_\varepsilon^2 & , k = 1 \\ \theta_1 \Theta_1 \sigma_\varepsilon^2 & , k = 11, 13 \\ -\theta_1 (1 + \theta_1^2) \sigma_\varepsilon^2 & , k = 12 \\ 0 & , k \text{ others} \end{cases}$$

4. ACF value of process  $\{Z_t\}$  for lag (time-distance)  $k$  is calculated using equation (8).

$$r_k = \text{Corr}(Z_t, Z_{t-k}) = \frac{\sum_{t=1}^{n-k} (Z_t - \bar{Z})(Z_{t-k} - \bar{Z})}{\sum_{t=1}^n (Z_t - \bar{Z})^2} \quad (8)$$

5. PACF value of process  $\{Z_t\}$  is calculated through Yule-Walker equation in equation (9).

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1} \rho_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1} \rho_j} \quad (9)$$

ACF value of process  $\{Z_t\}$  of multiplicative SARIMA model  $(0,0,1)(0,0,1)^{12}$  is

$$r_k = \begin{cases} 1 & , k = 0 \\ \frac{-\theta_1}{1 + \theta_1^2} & , k = 1 \\ \frac{\theta_1 \Theta_1}{(1 + \theta_1^2)(1 + \Theta_1^2)} & , k = 11, 13 \\ \frac{-\theta_1}{1 + \theta_1^2} & , k = 12 \\ 0 & , k \text{ others} \end{cases}$$

PACF value of process  $\{Z_t\}$  of multiplicative SARIMA model  $(0,0,1)(0,0,1)^{12}$  is calculated using equation (9), but the result is not given in this article.

## METHOD

The research methodology explains the research data, research steps by Box-Jenkins approach or approach. Lastly, an analysis was given related to the results of this research with

previous research results.

## RESEARCH DATA

Cilacap Regency is the largest regency located in the southwest part of Central Java Province. Cilacap has tropical climate with dry and rain seasons alternating annually. The rainfall in Cilacap has extreme seasonal variations in monthly rainfall. For example, in 2021 it had the smallest monthly rainfall in May with 201.8 mm and the lowest rainfall in November with 799.6 mm.

This research used secondary data in the form of data on rainfall in Cilacap Regency from January 2009 to December 2022. The data were obtained from Tunggul Wulung Station, Cilacap Regency. The research data were divided into two, training data to December 2021 (156 data or 93%) and testing data from January to December 2022 (12 data).

## Research Steps

The research steps were divided into two: model formulating steps by Box-Jenkins approach and forecasting by the model obtained. Box and Jenkins had developed a procedure called Box-Jenkins (BJ) procedure. BJ procedure is used to determine AR, MA, ARMA, or ARIMA model by data's behaviors and determine AR, MA order, and differencing orders for stationary data.

BJ procedure has been widely used in various time series studies using with SARIMA method for its capability of catching the trend of data pattern by evaluating pas data. The advantage of BJ procedure is that it reveals much information in time series data with the least possible parameters (Rosadi, 2022) and anticipates stationary and non-stationary time series and seasonal and non-seasonal elements.

The basis of Box-Jenkins approach consists of three stages (Sunariadi, 2022). Some authors included forecasting stages as part of Box-Jenkins approach stages, thus there are totally four stages. In this article, forecasting was included as part of the third stage.

First step was formulating SARIMA model. The model was formulated using steps following BJ procedures consisting of the following three stages. The first stage was model identification. In the identification stage, differencing ( $d$ ), seasonal differencing ( $D$ ), non-seasonal autoregressive ( $P$ ), seasonal autoregressive ( $P$ ), non-seasonal moving average ( $Q$ ) and seasonal moving average ( $Q$ ) orders were determined based on the collected historical data. The orders were identified through sample auto-correlation (SAC) or auto-correlation function (ACF) and sample partial auto-correlation (SPAC) or partial auto-correlation function (ACF)

diagrams. In this stage, some SARIMA models  $(p,d,q)(P,D,Q)^s$  were obtained based on ACF and PACF plots, thus the model were compared in view of p-value of each parameter in each of the SARIMA models  $(p,d,q)(P,D,Q)^s$  compared to the significance level. This way, the model identification model was also called candidate model determination stage. The steps of model identification model were:

- Observing data pattern based on time series plot;
- Transforming Box-Cox if the data were still not stationary against the variance;
- Based on ACF plot, if the data were still not stationary against non-seasonal mean, performing non-seasonal differencing.
- Based on ACF plot with data after non-seasonal differencing, seasonal differencing could be performed on the data if the data were still not stationary against seasonal mean;

The second stage estimated the parameters against the expected model obtained. Past data were used to estimate the identified parameters of forecasting models. Parameters could be estimated using maximum likelihood method or least square method. For the best model out of all candidate models, a model with lowest MSE value was chosen. The steps in the parameter estimation stage were:

- Identifying SARIMA model  $(p,d,q)(P,D,Q)^s$  in view of ACF and PACF plots;
- Comparing SARIMA model  $(p,d,q)(P,D,Q)^s$  which may possibly meet the criteria in view of p-value of each parameter formulated from the SARIMA model  $(p,d,q)(P,D,Q)^s$  which was possible if p-value of each parameter in a model is lower than significance level  $\alpha$ , thus the model could be the best candidate model;

The third stage was diagnostic examination, testing the accuracy of tentative models obtained in view of MAPE value in forecasting testing results to show the feasibility of the model. The next was parameter significance test and model suitability test on the best candidate SARIMA model. Any error of each candidate should meet the white noise and normally distributed assumptions. The last stage of this step was obtaining the best SARIMA model to be used for forecasting. It indicated that the selected model was fit. The steps to do in the third stage were as follows:

- Performing parameter significance test and model suitability test on the best candidate SARIMA model (residue must meet the white noise and normally distributed assumptions)
- Upon meeting the significance and model suitability tests, the best SARIMA model could be determined based on the lowest MSE value;
- Obtaining the best SARIMA model for forecasting.

The second step was forecasting using the SARIMA model obtained. The best (chosen) model was used for forecasting. In this stage, there was usually comparing the original data and the forecast values. The forecasting steps were as follows. First, testing the forecasting for data from January 2022 to December 2022 using the best calculated SARIMA model. Second, observing the MAPE value in the results of forecasting testing to show the model's feasibility. Third, performing forecasting for data from January 2023 to December 2024 using the best calculated SARIMA model.

### Analysis on Results against Previous Research

The third step was analysis on and comparison of the results with previous research regarding rainfall pattern and agricultural insurance.

## RESULTS AND DISCUSSION

The Result and Discussion explains the data and plot data, and final results of the use of BJ approach with rainfall data in the form of SARIMA model. The model obtained was then used to forecast future rainfall. The results of analysis forecast were based on previous research.

### Plot Data Collection

Figure 1 describes the historic data used in this research. The  $x$ -axis stated month and  $y$ -axis stated volume of corresponding monthly rainfall. The historical data pattern in Figure 1 shows almost the same seasonal variation annually. Therefore, SARIMA method was chosen for forecasting model based on the historical data.

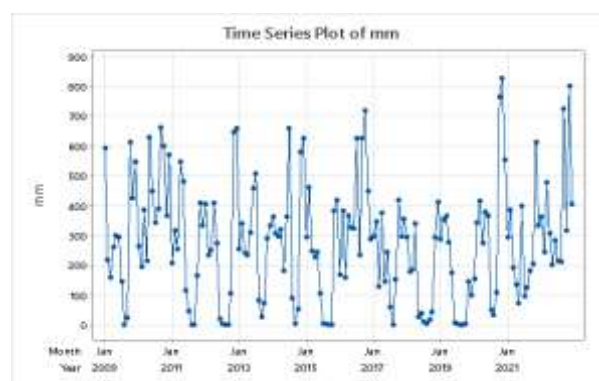


Figure 1. Plot data on rainfall in Cilacap Regency

### Box-Jenkins Procedure

Box-Jenkins procedure used four stages: identification, estimation, diagnosis and

forecasting. Some stages contained more than one working step.

### Model Identification Stage

The first stage was temporary model identification. Identification was conducted by determining the stationary properties of the time series data for forecasting in mean and variance. The requirements for stationary properties must be satisfied since SARIMA model only applies to stationary data.

The concept of stationary can statistically be explained as follows. If a diagram is created for some time series data and there is not clear change to the mean from time to time, the stationary of time series data is on its mean. If the diagram of time series data does not show any clear change in variance from time to time, the time series data are stationary on variance.

**Table 1. Struktur ACF dan PACF pada model ARIMA**

| Model                                                | ACF                      | PACF                     |
|------------------------------------------------------|--------------------------|--------------------------|
| Autoregressive<br>$AR(p)$                            | dies down to<br>0        | cut off after<br>lag $p$ |
| Moving<br>Average $MA(q)$                            | cut off after<br>lag $q$ | dies down<br>to 0        |
| Autoregressive<br>Moving<br>Average ARMA<br>$(p, q)$ | dies down to<br>0        | cut off<br>after lag $p$ |

A time series data model must satisfy stationary assumption, thus a method is needed to eliminate non-stationary properties of the data. The method used was differencing for non-stationary data in mean. Meanwhile, transformation method was used for non-stationary time series data against variance. After the data were stationary, the next step was to observe ACF and PACF plots to identify the order of AR and MA models with ACF and PACF plots (Wei, 2006).

Figure 1 shows that the data had constant tendency around mean value with relatively fixed amplitude. The data pattern does not show ascending or descending trend. Visually, this shows that the data on rainfall in Cilacap were stationary in mean.

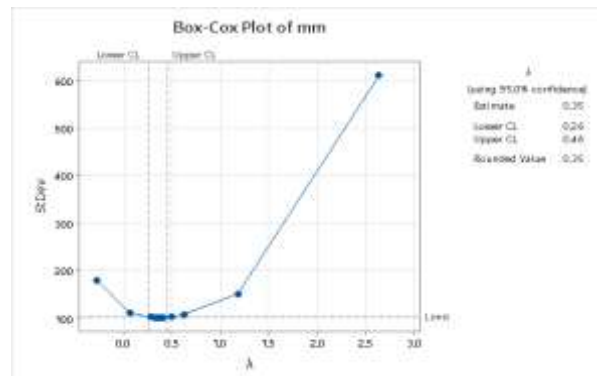


Figure 2. Plot Box-Cox for data on rainfall in Cilacap Regency

Further, the data's stationary properties in variance were conducted based on the lambda value and ACF plot in Figure 2. The data were declared stationary in variance if lambda value were higher or equal to 1.

Figure 2 shows the data before it were stationary against variance since  $\lambda = 0.35$ . The data needed to be transformed into stationary in variance with transformation in which  $Z_t^{(\lambda)} = (Z_t)^\lambda$  with  $Z_t$  being the data on rainfall for  $t=1,2,\dots$ . For example, rainfall data for January 2009 ( $t=1$ ) were  $Z_1 = 594.5$ . The transformation results were  $Z_1^{(\lambda)} = (Z_1)^\lambda = 594.5^{0.35} = 9.3530$ . The other data transformation were conducted in the same way. The transformation results for three first genuine data and last data are available in Table 2.

Table 2. Actual and Transformation Rainfall Data

|                  | Actual Data<br>(mm) | Transformation<br>Data (mm) |
|------------------|---------------------|-----------------------------|
| January<br>2009  | 594.5               | 9.3530                      |
| February<br>2009 | 219.4               | 6.5983                      |
| March 2009       | 160.9               | 6.5983                      |
| .                | .                   | .                           |
| .                | .                   | .                           |
| March 2009       | 160.9               | 6.5983                      |

The plot of data on transformation results is made available in Figure 3. The plot of transformation data shows seasonal pattern for each year. The plot of data also shows constant tendency around mean value with relatively fixed amplitude.

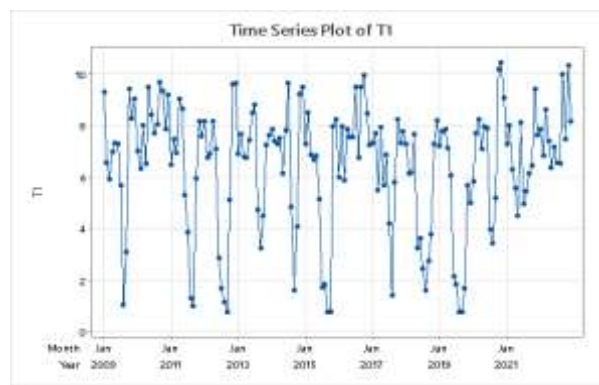


**Figure 3.** Plot rainfall data on rainfall in Cilacap Regency

Further, referring to Figure 4, it resulted in lambda value 1. Thus, the data of transformation results were stationary against variance.

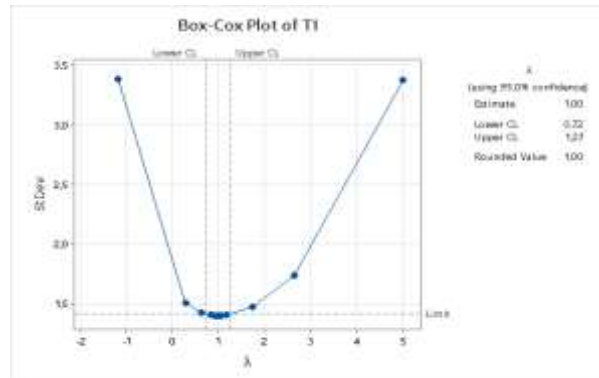


**Figure 4.** Plot Box-Cox for rainfall transformation in Cilacap Regency

The next step was to determine whether the data were already stationary against the mean or not. The stationary data in mean could be observed from ACF plot. The lag in ACF plot determined the autocorrelation value in the data.

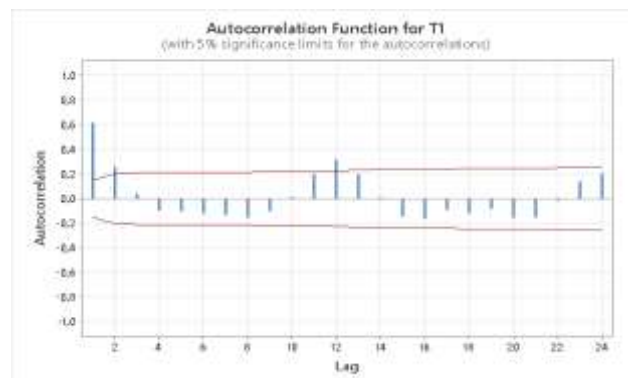


Figure 5. **ACF Plot** for rainfall transformation data in Cilacap Regency

Figure 5 shows that the data were already stationary in non-seasonal mean and already stationary in seasonal mean with period  $s=12$ . Autocorrelation value in lag 12 was 0.317832. Thus, the data could be used directly for SARIMA model.

Based on Figure 5, the seasonal ACF value shows the data were cut off after lags 1 and 2. The situation identified the form of non-seasonal MA with  $q=2$  and seasonal MA with  $Q=1$ .

Figure 6 shows PACF plot. Based on Figure 6 the data were not cut off on lags 12, 24, or its multiplications. This result identified the form of seasonal AR with  $P=0$ .

From the non-seasonal ACF plot results on initial lags, which were lag 1 and 2 significantly different from zero (cut off after lag 2) that identified the form of AR with  $p=1$  and  $p=2$  for non-seasonal pattern. Therefore, the initial conjecture of the model suitable for the data were  $SARIMA(2,0,2)(0,0,1)^{12}$ . Three others model that could be formed were  $SARIMA(1,0,1)(0,0,1)^{12}$ ,  $SARIMA(2,0,1)(0,0,1)^{12}$ , and  $SARIMA(1,0,2)(0,0,1)^{12}$ .

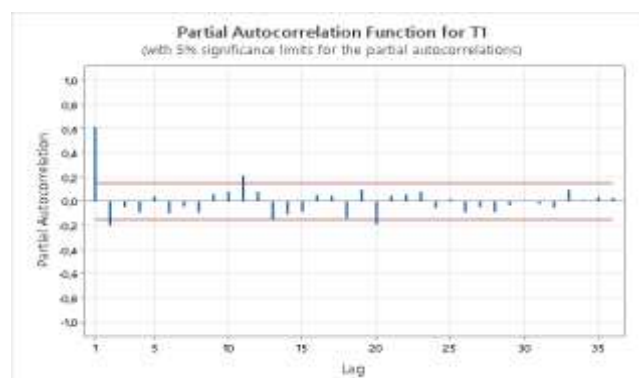


Figure 6. **PACF Plot** after one seasonal differencing

All candidate SARIMA models were selected based on p-value of each parameter for each model. Model with lower p-value of each parameter than significance level was chosen as the model suitable for the data. The model was then tested for suitability for all appropriate models and a model with the lowest mean square error (MSE) was chosen to be the best model.

### Parameter Estimation Stage

The identification stage produced some candidate SARIMA models for the data researched. The parameter estimations stage produced one best SARIMA model based on model with the lowest MSE value. Therefore, the final goal of parameter estimation stage was the best SARIMA model.

The estimation stage started with significance test, followed by model suitability test, residual model suitability test and residual model normality test. The last work was choosing the best SARIMA model. This research used criteria of lowest MSE value to determine the best SARIMA model.

#### Parameter Significance Test on All Candidate SARIMA Models

The appropriate SARIMA model test to model the rainfall data in this research was determine based on comparison of p-value with the significance level chosen. The proposed hypotheses for parameter significance test were:

$H_0$ : parameter  $\phi_p, \theta_p, \Theta_p$  is not significant in the model.

$H_1$ : Parameter  $\phi_p, \theta_p, \Theta_p$  is significant in the model.

The other test that used to parameter significance test is unit root test with the hypothesis:

$H_1$  :  $\delta = 0$  (The variable  $Z_t$  contain a unit root, the variable  $Z_t$  does not stationary)

$H_1$  :  $\delta \neq 0$

(The variable  $Z_t$  does not contain a unit root, the variable  $Z_t$  stationary).

The criteria for rejection of  $H_0$  were  $p\text{-value} < \alpha$ . This research used significance level  $\alpha = 0.05$ . If  $p\text{-value} < 0.05$ , the model parameter was significant or constant in the model.

Table 4 shows MINITAB output for the four candidates SARIMA models obtained based on the ACF and PACF plots in identification stages. Table 4 also summarized estimated parameter, p-value and MSE values.

**Table 4. Parameter estimation, significant test and MSE value for SARIMA models**

| SARIMA Model          | Coefficient            | P-value | MSE     |
|-----------------------|------------------------|---------|---------|
| $(1,0,1)(0,0,1)^{12}$ | $\phi_1 = 0.9501$      | 0.000   | 3.69851 |
|                       | $\theta_1 = -0.0929$   | 0.263   |         |
|                       | $\Theta_1 = -0.4215$   | 0.000   |         |
| $(2,0,1)(0,0,1)^{12}$ | $\phi_1 = 1.4640$      | 0.000   | 3.37767 |
|                       | $\phi_2 = -0.4641$     | 0.000   |         |
|                       | $\theta_1 = 0.9901088$ | 0.000   |         |
|                       | $\Theta_1 = -0.3477$   | 0.000   |         |
| $(1,0,2)(0,0,1)^{12}$ | $\phi_1 = 0.99946$     | 0.000   | 3.58033 |
|                       | $\theta_1 = 0.3031$    | 0.000   |         |
|                       | $\theta_2 = 0.4479$    | 0.000   |         |
|                       | $\Theta_1 = -0.3200$   | 0.000   |         |
| $(2,0,2)(0,0,1)^{12}$ | $\phi_1 = 1.4501$      | 0.000   | 3.20174 |
|                       | $\phi_2 = -0.4504$     | 0.000   |         |
|                       | $\theta_1 = 0.73831$   | 0.000   |         |
|                       | $\theta_2 = 0.2517$    | 0.000   |         |
|                       | $\Theta_1 = -0.3319$   | 0.000   |         |

Based on Table 4, SARIMA model  $(1,0,1)(0,0,1)^{12}$  produced significant estimated parameter  $AR(p=1)$  and  $MA(Q=1)$  since  $p\text{-value} < 0.05$ . However, the parameter in  $MA(q=1)$  was insignificant since  $p\text{-value} > 0.05$ . Consequently, SARIMA  $(1,0,1)(0,0,1)^{12}$  was not suitable for a model for the rainfall data used in this research.

The calculation results in Table 4 conclude that all parameters in SARIMA model  $(2,0,1)(0,0,1)^{12}$  are constant in-time (constant through time). This is shown as all p-values are lower than 0.05. Thus, SARIMA  $(2,0,1)(0,0,1)^{12}$  was suitable for a model of data researched. Furthermore, we may conclude that SARIMA model  $(1,0,2)(0,0,1)^{12}$  is suitable for possible model and SARIMA model  $(2,0,2)(0,0,1)^{12}$  is suitable for model in the data researched. This is identified with p-values in Table 4 which are entirely lower than significance level 0.05.

The parameter significance test resulted in three models usable for modeling the data, namely SARIMA  $(2,0,1)(0,0,1)^{12}$ , SARIMA  $(1,0,2)(0,0,1)^{12}$  and SARIMA  $(2,0,2)(0,0,1)^{12}$ . The next step was testing model suitability for the three chosen candidate SARIMA models. This model suitability test covered residual suitability test and residual normality test.

### Error Model Fit Test

Residual model suitability test is also called white noise test. White noise is random data that fulfilled the assumption of stationary data. White noise testing uses the Ljung-Box test. The hypotheses for the residual model suitability test were:

$$H_0: \rho_1 = \rho_2 = \dots = \rho_k = 0$$

(error autocorrelation is not significant).

(model error meets white noise requirements)

$$H_1: \text{There is minimum one } \rho_i \neq 0$$

(error autocorrelation is significant).

(model error does not meet white noise requirements)

The criteria for rejecting  $H_0$  were  $p\text{-value} < 0.05$ . Based on the Minitab output, it resulted in Ljung-Box test or Modified Box-Pierce test for the two SARIMA models. The research results were summarized in Table 5.

**Table 5. Box-Pierce Modified test for the three SARIMA models**

| Lag | p-value for Box-Pierce Modified Test |                       |                       |
|-----|--------------------------------------|-----------------------|-----------------------|
|     | SARIMA Model                         |                       |                       |
|     | $(2,0,1)(0,0,1)^{12}$                | $(2,0,2)(0,0,1)^{12}$ | $(1,0,2)(0,0,1)^{12}$ |
| 12  | 0.057                                | 0.743                 | 0.015                 |
| 24  | 0.022                                | 0.132                 | 0.004                 |
| 36  | 0.017                                | 0.149                 | 0.002                 |
| 48  | 0.006                                | 0.149                 | 0.001                 |

Based on Table 5, the residual autocorrelation of the two models showed higher p-value than 0.05. The decision obtained  $H_0$  accepted, which means there was no correlation between lags, or there was no residual autocorrelation or residual autocorrelation was insignificant. The

conclusion of residual suitability test was SARIMA model  $(2,0,2)(0,0,1)^{12}$  was suitable for meeting the white noise requirements.

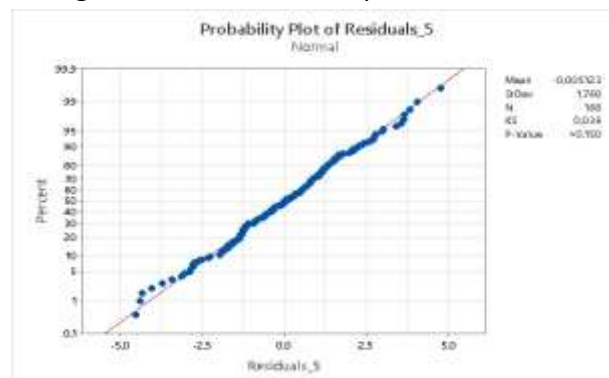
### Error Model Normality Test

The hypotheses for the residual model (white noise) normality test were

$H_0$ : Residual model was normally distributed.

$H_1$ : Residual model was normally distributed.

The criteria for rejecting  $H_0$  were  $p\text{-value} < 0.05$ . The test was conducted using Kolmogorov-Smirnov Test. Figure 7 shows residual plot for the SARIMA model.



**Picture 7.** Probability Plot Error for SARIMA  $(2,0,2)(0,0,1)^{12}$

Based on Figure 7,  $p\text{-value}$  was higher than 0.05, thus  $H_0$  was accepted. It was concluded that residual SARIMA model  $(2,0,2)(0,0,1)^{12}$  met the normally distributed assumption.

### Best Choice of Model

The last work was to choose the most appropriate SARIMA model to model the rainfall data. The choice was based on the lowest MSE value. However, since there was only one model, the model would automatically be chosen. By calculation, SARIMA model  $(2,0,2)(0,0,1)^{12}$  had MSE value 3.20174.

Further, since all model parameters were significant, the residual model met the requirements of white noise, normally distributed residual model, and with lowest MSE, thus we may conclude that SARIMA model  $(2,0,2)(0,0,1)^{12}$  was the model that could be used to model the research's rainfall data.

### Diagnostic Checking Stage

By calculation, the best model obtained for forecasting was SARIMA $(2,0,2)(0,0,1)^{12}$ . SARIMA $(2,0,2)(0,0,1)^{12}$  could be formulated in the following equation by taking  $(p,d,q)(P,D,Q)^{12} = (2,0,2)(0,0,1)^{12}$ .

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t$$

For  $d=0, D=0$  obtained

$$\Phi_p(B^s)\phi_p(B)Z_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t$$

For  $p=2, P=0, q=2, Q=1, s=12$  obtained

$$(1-\phi_1B-\phi_2B^2)Z_t = (1-\theta_1B-\theta_2B^2)(1-\Theta_1B^{12})\varepsilon_t$$

$$(1-\phi_1B-\phi_2B^2)Z_t = (1-\theta_1B-\theta_2B^2-\Theta_1B^{12}+\phi_1\Theta_1B^{13}+\phi_2\Theta_1B^{14})\varepsilon_t$$

$$Z_t - \phi_1Z_{t-1} - \phi_2Z_{t-2} = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \Theta_1\varepsilon_{t-12} + \phi_1\Theta_1\varepsilon_{t-13} + \phi_2\Theta_1\varepsilon_{t-14}$$

$$Z_t = \phi_1Z_{t-1} + \phi_2Z_{t-2} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \Theta_1\varepsilon_{t-12} + \phi_1\Theta_1\varepsilon_{t-13} + \phi_2\Theta_1\varepsilon_{t-14}$$

Substitute the coefficients on Table 1 to SARIMA $(2,0,2)(0,0,1)^{12}$  in equation (10):

$$Z_t = 1.4501Z_{t-1} - 0.4504Z_{t-2} + \varepsilon_t - 0.73831\varepsilon_{t-1} - 0.2517\varepsilon_{t-2} + 0.3319\varepsilon_{t-12} - 0.245045089\varepsilon_{t-13} - 0.083539234\varepsilon_{t-14}.$$

Based on the results of elaboration of SARIMA model  $(2,0,2)(0,0,1)^{12}$  in Equation (11), 2022 forecast was resulted. Furthermore,  $Z_{157}$  value was calculated, which was forecast for January 2022. Equation (11) presented result of equation (12).

$$Z_{157} = 1.4501Z_{156} - 0.4504Z_{155} + \varepsilon_{157} - 0.73831\varepsilon_{156} - 0.2517\varepsilon_{155} + 0.3319\varepsilon_{145} - 0.245045089\varepsilon_{144} - 0.083539234\varepsilon_{143}.$$

Substitution of the following values into equation (12) resulted in  $Z_{157} = 9.061150$

|           |           |                     |                     |                     |                     |                     |                     |
|-----------|-----------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| $Z_{156}$ | $Z_{155}$ | $\varepsilon_{157}$ | $\varepsilon_{156}$ | $\varepsilon_{155}$ | $\varepsilon_{145}$ | $\varepsilon_{144}$ | $\varepsilon_{143}$ |
| 7.6174    | 9.4102    | 1.42308             | -1.18287            | 2.75734             | -0.57714            | 1.17002             | 0.98507             |

Meanwhile, rainfall forecast for January 2022 was calculated using equation  $z_t^{(1/\lambda)} = (z_1)^{1/\lambda}$ , resulting in  $z_{157}^{(1/0.35)} = 7.849461^{2.857143} = 360.3175$ . Complete results for 2022 forecast are presented in Table 6. Table 6 displays the results of rainfall forecasting testing calculated using SARIMA model  $(2,0,2)(0,0,1)^{12}$  or Equation (12).

**Table 6. Rainfall Forecast Testing Results with the SARIMA model  $(2,0,2)(0,0,1)^{12}$** 

| Period<br>$t$ | Month<br>2022 | Transformational<br>Rainfall Forecast<br>(mm) | Precipitation<br>Forecast<br>(mm) | Actual<br>Rainfall<br>(mm) | Actual Rainfall<br>Transformation<br>(mm) |
|---------------|---------------|-----------------------------------------------|-----------------------------------|----------------------------|-------------------------------------------|
| 7             | January       | 7.849461                                      | 360.3175                          | 364.4                      | 7.880476                                  |
| 8             | February      | 6.840854                                      | 243.2370                          | 245.8                      | 6.865998                                  |
| 9             | March         | 8.628125                                      | 472.1142                          | 477.7                      | 8.663719                                  |
| 0             | April         | 7.394130                                      | 303.7628                          | 307.1                      | 7.422461                                  |
| 1             | May           | 6.385268                                      | 199.7616                          | 201.8                      | 6.407999                                  |
| 2             | June          | 7.185981                                      | 279.9647                          | 283.0                      | 7.213155                                  |
| 3             | July          | 6.541013                                      | 214.0003                          | 216.2                      | 6.564467                                  |
| 4             | August        | 6.510079                                      | 211.1214                          | 213.3                      | 6.533514                                  |
| 5             | September     | 9.983342                                      | 716.2658                          | 725.3                      | 10.027230                                 |
| 6             | October       | 7.467366                                      | 312.4383                          | 351.9                      | 7.784787                                  |
| 7             | November      | 10.329130                                     | 789.4519                          | 799.6                      | 10.375410                                 |
| 8             | December      | 8.160041                                      | 402.5644                          | 407.2                      | 8.192807                                  |

### Forecasting using SARIMA $(2,0,2)(0,0,1)^{12}$

Based on Table 6, MAPE value = 0.06967% was resulted, calculated using equation (13)

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^n \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \quad (13)$$

where  $Z_t$  was transformation of actual rainfall and  $\hat{Z}_t$  was forecast of transformation rainfall in Table 6. MAPE value obtained was quite low. SARIMA model  $(2,0,2)(0,0,1)^{12}$  could be used in forecasting process. MAPE value obtained shows good model forecasting ability. SARIMA model  $(2,0,2)(0,0,1)^{12}$  was used to forecast rainfall from January 2023 to December 2024.

For example, January 2023 forecast for  $t=169$ . Equation (11) resulted in equation (14).

$$Z_{169} = 1.4501Z_{168} - 0.4504Z_{167} + \varepsilon_{169} - 0.73831\varepsilon_{168} - 0.2517\varepsilon_{167} + 0.3319\varepsilon_{157} - 0.245045089\varepsilon_{156} - 0.083539234\varepsilon_{155}.$$

Substitution of the following values into equation (14) resulted in  $Z_{169} = 7.35775321$ .

$$\begin{array}{cccccccc} Z_{168} & Z_{167} & \varepsilon_{169} & \varepsilon_{168} & \varepsilon_{167} & \varepsilon_{157} & \varepsilon_{156} & \varepsilon_{155} \\ 8.1600 & 10.3292 & 0 & -0.533999 & 2.975297 & 1.423082 & -1.182873 & 2.757342 \end{array}$$



Meanwhile, rainfall forecast for January 2023 was calculated using equation  $z_t^{(1/\lambda)} = (z_1)^{1/\lambda}$ , resulting in  $z_{169}^{(1/0,35)} = 7.35775321^{2.857143} = 299.512553$ . Complete results of rainfall forecasting from January 2023 to December 2024 were available in Table 7.

**Table 7. Rainfall Forecast with SARIMA $(2,0,2)(0,0,1)^{12}$  and the results of the transformation**

| Period<br>$t$ | Month-<br>Year    | Transformational<br>Rainfall<br>Forecast<br>(mm) | Precipitation<br>Forecast<br>$z_t^{2,857143}$ (mm) |
|---------------|-------------------|--------------------------------------------------|----------------------------------------------------|
| 169           | January<br>2023   | 7.35775321                                       | 299.512553                                         |
| 170           | February<br>2023  | 6.62827447                                       | 222.258635                                         |
| 171           | March<br>2023     | 7.26210000                                       | 288.521319                                         |
| 172           | April<br>2023     | 6.82703474                                       | 241.835716                                         |
| 173           | May<br>2023       | 6.60043993                                       | 219.602321                                         |
| 174           | June<br>2023      | 6.49828710                                       | 210.030648                                         |
| 175           | July<br>2023      | 6.48103939                                       | 208.441823                                         |
| 176           | August<br>2023    | 6.40549325                                       | 201.574714                                         |
| 177           | September<br>2023 | 7.53994779                                       | 321.193544                                         |
| 178           | October<br>2023   | 6.84403536                                       | 243.560318                                         |
| 179           | November<br>2023  | 7.43764408                                       | 308.898308                                         |

|     |                  |            |            |
|-----|------------------|------------|------------|
| 180 | cember<br>2023   | 6.87353217 | 246.571507 |
| 181 | January<br>2024  | 6.49969424 | 210.160618 |
| 182 | February<br>2024 | 6.37397809 | 198.754065 |
| 183 | March<br>2024    | 6.31544334 | 193.583456 |
| 184 | April<br>2024    | 6.28718466 | 191.118879 |
| 185 | May<br>2024      | 6.27257079 | 189.852374 |
| 186 | June<br>2024     | 6.26410694 | 189.121359 |
| 187 | July<br>2024     | 6.25841558 | 188.630832 |
| 188 | August<br>2024   | 6.25397467 | 188.248654 |
| 189 | ptember<br>2024  | 6.25009829 | 187.915470 |
| 190 | October<br>2024  | 6.24647734 | 187.604588 |
| 192 | vember<br>2024   | 6.24297253 | 187.303994 |
| 192 | cember<br>2024   | 6.23952106 | 187.008283 |

## DISCUSSION

Rainfall or precipitation is the amount of rainwater falling in a certain area within a certain time. The instrument used to measure the amount of rainfall was called rain gauge. This instrument consists of funnel and tube (Wei, 2006). Rainfall according to BMKG is divided into four (Table 8).

**Table 8. Classification of rainfall according to BMKG**

| Rainfall/Month | Category     |
|----------------|--------------|
| 0 – 100 mm     | Low          |
| 101 – 300 mm   | Intermediate |
| 301 – 500 mm   | High         |
| > 500 mm       | Very High    |

Oldeman divided rainfall into three: dry, humid and wet rainfalls. Referring to Oldeman (2006), paddy's need for water is 200 mm/month, meanwhile, secondary crops' need is 120 mm/month. Consequently, in Oldeman's classification a month is wet if there is over 200 mm/month rainfall, and is dry if the rainfall is less than 100 mm/month. Referring to (Wei, 2006), Table 9 displays rainfall classification according to Oldeman.

Practically, Oldeman's classification is more appropriately applied to optimal rainfall analysis for diverse agricultural commodities. Paddy can grow optimally when there is about 200 mm monthly rainfall available which in Oldeman's category is the upper limit of humid category, but is of medium category according to BMKG. Statistically, with tolerance averagely  $\pm 1.645$  standard deviation, the chance for optimal rainfall is 95%. Taking standard deviation 30 mm, the optimal rainfall interval for paddy's growth is (150 , 250) mm per month.

**Table 9. Classification of rainfall according to Oldeman (Lakitan, 2002)**

| Rainfall/Month | Category |
|----------------|----------|
| < 100 mm       | Dry      |
| 100 – 200 mm   | Moist    |
| > 200 mm       | Wet      |

Optimal rainfall is a condition when paddy can grow well. Rainfall higher than 250 mm/month (Wei, 2006) causes harvest failure due to flood and rainfall lower than 150 mm/month causes harvests failure due to drought. In the concept of rainfall index based agricultural insurance, optimal rainfall is a condition when compensation is not paid. The interval limits of optimal rainfall are positioned as the trigger, which is rainfall that for the first time agricultural insurance participant obtains compensation. Thus, if rainfall is less than 150 mm or over 250 mm, insurance farmer-participant will be compensated. If rainfall ranges between 150 and 250 mm, farmer will not be compensated (Figure 8).

### Compensation

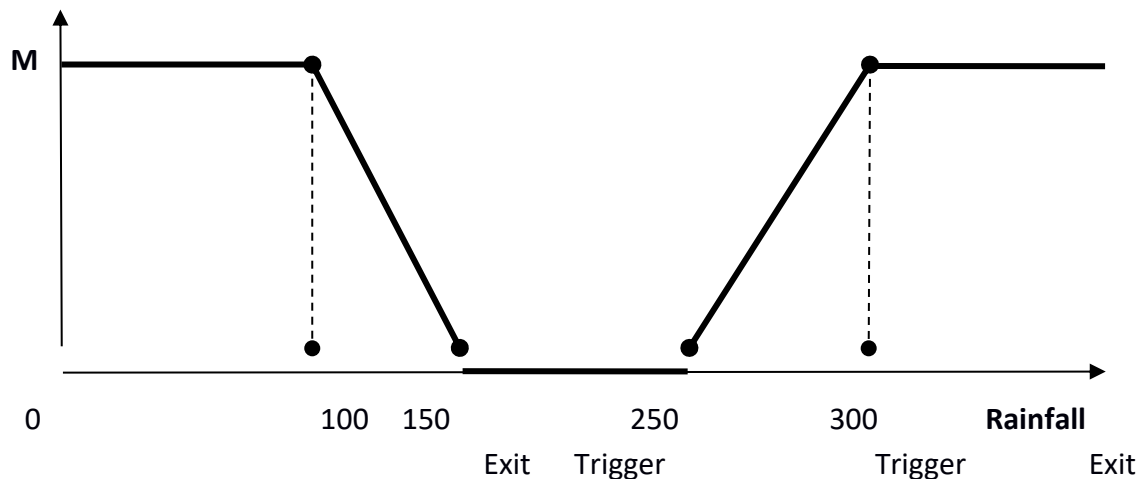


**Figure 8.** The concept of compensation for agricultural insurance based on the rainfall index

The amount of compensation is divided into 3 parts: (1) no compensation, (2) partial compensation, and (3) maximum compensation (Wei, 2006). Maximum compensation ( $M$ ) is determined as the cost incurred for planting a hectare of land per planting season. Therefore, farmers are expected to replant their land in case of severe harvest failure. Partial compensation in Figure 8 is, meanwhile, declared as a straight line of which value can be calculated using linear function equation.

Referring to Figure 8, there is exit point determined, for example 100 and 300 mm/month. Exit point is rainfall which for the first time maximum compensation is paid. Based on Figure 8, partial compensation is given if rainfall is  $(100, 150)$  or  $(250, 300)$  mm per month. Figure 8 is actually a combination of two types of insurance, when rainfall keeps descend and ascending. Thus, there are two concepts of compensation payment (Table 10).

**Table 10.** Concept of compensation payment

| Compensation      | Interval (mm/month) |                 |
|-------------------|---------------------|-----------------|
|                   | Drought Insurance   | Flood Insurance |
| No Indemnity      | $> 150$             | $< 250$         |
| Partial Indemnity | $(100, 150)$        | $(250, 300)$    |
| Maximun Indemnity | $< 100$             | $> 300$         |

The forecasting results in Table 7 present rainfall data between 187 – 311 mm per month. This means that the rainfall in Cilacap tended to be of medium rainfall classification (BMKG classification) or humid and wet classification (Oldeman classification). Based on 156 training data out of 168 data (93%), mean rainfall was 271 mm, lowest data 0.05 (September 2012) and highest rainfall 826,7 mm (November 2020). The mean rainfall in Cilacap was of medium category, while the lowest and highest data show possible drought and flood. These conditions make Cilacap Regency are quite suitable for paddy agriculture and rainfall index based agricultural insurance program to be implemented onto it.

## CONCLUSION

Based on the discussion results, there are three main conclusions as follows:

1. The rainfall forecasting model in Cilacap using training data from January 2009 to December 2021 produced SARIMA model  $(2,0,2)(0,0,1)^{12}$
2. The results of rainfall forecasting in Cilacap using testing data from January 2022 to December 2022 produced MAPE value 0.06967%. This result shows high accuracy between the model and the actual data.
3. Water available derived from rainfall for agriculture is quite important for Cilacap area. Rainfall forecasting is very important in relation to rainfall index based agricultural insurance. Seasonal rainfall predicted with SARIMA model  $(2,0,2)(0,0,1)^{12}$  from January 2023 to December 2024 shows no symptom of anomaly (extremely low and high). This condition is quite good for rainfall index based agricultural insurance implementation.

## REFERENCE

- Aldrian, E., Budiman., and Karmini, M. (2011). *Adaptasi dan Mitigasi Perubahan Iklim di Indonesia* [Climate Change Adaptation and Mitigation in Indonesia]. Pusat Perubahan Iklim dan Kualitas Udara Kedeputan Bidang Klimatologi, Badam Meteorologi, Klimatologi, dan Geofisika. Jakarta.
- Ariyanto, S.E. (2010). Kajian Dampak Perubahan Iklim terhadap Produktifitas Kacang Hijau (*Phaseolus Radiates L.*) di Lahan Kering [Study of the Impact of Climate Change on the Productivity of Green Beans (*Phaseolus Radiates L.*) in Dry Land]. *Sains dan Teknologi*, 3(2): 1-10. <https://eprints.umk.ac.id/89/>.
- Aswi and Sukarna. (2006). *Analisis Deret Waktu: Teori dan Aplikasi* [Time Series Analysis: Theory and Applications]. Makasar: Andira Publisher.
- Brockwell, P.J. and Davis, R.A. (1996). *Introduction to Time Series and Forecasting*. New York:



Springer Verlag.

- Ervina, M. E., Silvi, R., and Wibisono, I. R. N. (2018). Peramalan Jumlah Penumpang Kereta Api di Indonesia dengan Resilient Back-Propagation (RProp) Neural Network [Forecasting the Number of Train Passengers in Indonesia with the Resilient Back-Propagation (RProp) Neural Network]. *Jurnal Matematika "MANTIK"*, 4(2): 90–99. DOI: <https://doi.org/10.15642/mantik.2018.4.2.90-99>.
- Hatasuhut, A., Aggraeni, W., and Tyasnurita, R. (2014). Persediaan Baan Baku Produksi Plastik Blowing dan Inject Menggunakan Metode ARIMA (Autoregressive Integrated Moving Average) di CV Asia [Inventory of Raw Materials for Blowing and Inject Plastic Production Using the ARIMA (Autoregressive Integrated Moving Average) Method at CV Asia]. *Jurnal Teknik ITS*, 3(2): 169-174. DOI: <https://doi.org/10.12962/j23373539.v3i2.8114>.
- Lakitan, B. (2002). *Dasar-Dasar Klimatologi [Fundamentals of Climatology]*. Jakarta: PT. Raja Grafindo Persada.
- Makridakis, S., Wheelwright S.C., and McGee, V.E. (1983). *Metode dan Aplikasi Peramalan [Forecasting Methods and Applications]*. Jakarta: Penerbit Erlangga; 2020.
- Montgomery, D.C. (2008). *Introduction to Time Series Analysis and Forecasting*. New York: John Wiley and Son, Inc.
- Multiningsih, S.E., and Saleh, M. (2022). Forecasting the Number of Ship Passengers with SARIMA Approach (Case Study: Semayang Port, Balikpapan City) [Forecasting the Number of Ship Passengers with the SARIMA Approach (Case Study: Semayang Port, Balikpapan City)]. *Jurnal dan Aplikasi Matematika*, 6(4): 1060-1080. DOI: <https://doi.org/10.31764/jtam.v6i4.10211>.
- Prabowo, A., Pratikno, B., Sukono, and Prayogo, I.H. (2019). Determining Sustainable Rice Farming through Supply Chain Risk Management: A Case Study in Central Java, Indonesia. *International Journal of Supply Chain Management*, 8(3): 164-171. DOI: <https://ojs.excelingtech.co.uk/index.php/IJSCM/article/view/3108/1634>.
- Prabowo, A., Mamat, M., and Sukono. (2019). Model of Rice Farm Insurance to Reduce Losses Due to Harvest Failure. *International Journal of Recent Technology and Engineering*, 8(2S7): 231-236. DOI: <https://doi.org/10.35940/ijrte.B1059.0782S719>.
- Prabowo, A., Zakaria, Z.A., Mamat, M., Sukono, Riyadi, S., and Bon, A.T. (2020). Determination of Agricultural Insurance Premium Prices Based on Rainfall Index with Formula Cash-or-Nothing Put Option. *Proceeding of the International Conference on Industrial Engineering and Operations Management (IEOM)*, December 8-14, 2020, Harare, Zimbabwe, pp. 1775-1783. <http://www.ieomsociety.org/harare2020/papers/427.pdf>





- Prabowo, A. Mamat, M., and Sukono. (2023). Determination of the Amount of Premium and Indemnity in Shallot Farming Insurance. *Universal Journal of Agricultural Research*, 11(2): 322-335. DOI: [https://10.13189/ujar.2023.110210](https://doi.org/10.13189/ujar.2023.110210).
- Purnama, D. I. (2022). Peramalan Curah Hujan di Kabupaten Parigi Moutong Menggunakan Model Seasonal Autoregressive Integrated Moving Average (SARIMA) [Forecasting Rainfall in Parigi Moutong Regency Using the Seasonal Autoregressive Integrated Moving Average (SARIMA) Model]. *Jurnal Ilmiah Matematika dan Terapan*, 18(2): 136-147. DOI: <https://doi.org/10.22487/2540766X.2022.v18.i2.15652>.
- Purwandari, A.E.D. (2019). Pemodelan dan Peramalan Indeks Harga Konsumen (IHK) Kota Surabaya Sampit dengan Seasonal ARIMA (SARIMA) [Modeling and Forecasting of the Sampit City Consumer Price Index (CPI) with Seasonal ARIMA (SARIMA)]. *Jurnal Derivat*, 6(2): 61-72. DOI: <https://doi.org/10.31316/j.derivat.v6i2.497>.
- Rosadi, D. (2022). Analisis Runtun Waktu dan Aplikasinya dengan R [Time series analysis and its application with R]. Yogyakarta: Gajah Mada University Press.
- Sunariadi, N.M., Intan, P.K. Novitasari, D.C.R., and Hariningsih, Y. (2022). Prediksi Produksi Bawang Merah di Kabupaten Nganjuk dengan Metode Seasonal ARIMA (SARIMA) [Prediction of Shallot Production in Nganjuk Regency with the Seasonal ARIMA Method (SARIMA)]. *Transformasi: Jurnal Pendidikan Matematika dan Matematika*, 6(1): 49-60. DOI: <https://doi.org/10.36526/tr.v%vi%i.1672>.
- Wei, W.W.S. 2006. *Time Series Analysis Univariate and Multivariate Methods*. New York: Addison Wesley.

