PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 05 No. 1, April 2026
Pages 75-86

Rainfall Prediction in Central Maluku Regency using The Autoregressive Moving Average (ARMA) Model Approach

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Abstract

Rainfall is one of the main indicators in regional climate analysis because its distribution and intensity reflect seasonal patterns, climate variability, and long-term climate change. Central Maluku Regency experiences fluctuating and unpredictable rainfall patterns influenced by geographical factors. This study aims to forecast rainfall in Central Maluku Regency using the Autoregressive Moving Average (ARMA) model. The data were obtained from the Central Statistics Agency (BPS) and consist of monthly rainfall observations from January 2019 to October 2024. The analysis procedure included stationarity testing using the Augmented Dickey-Fuller (ADF) test, model identification, parameter estimation and significance testing, as well as residual diagnostic testing. The results show that the ARMA(1,0) model is the most suitable model for forecasting rainfall data in Central Maluku Regency. The model produced a Mean Absolute Percentage Error (MAPE) value of 43.24%, indicating a reasonably accurate forecasting performance. The findings suggest that the ARMA model can be used as an alternative approach for rainfall forecasting and may support climate-based planning and decision-making in Central Maluku Regency, particularly in the agricultural and disaster mitigation sectors.

Keywords: *ARMA, Central Maluku, Forecasting, Rainfall.*

: https://doi.org/10.30598/parameterv5i1pp75-86

Research Article · Open Acces
Email: jurnalparameter@gmail.com
Homepage: https://ojs3.unpatti.ac.id/index.php/parameter

Submitted: July 2025
Accepted: April 2026

1. INTRODUCTION

According to the Meteorology, Climatology, and Geophysics Agency (BMKG), Rainfall (mm) is the height of rainwater accumulated in rain reservoirs in flat areas that do not absorb, do not permeate and do not flow. A millimeter of rain means that on a flat square meter, rainwater is stored as high as one millimeter or the equivalent of a liter of rainwater [1]. Research related to rainfall is very important to be carried out so that we can reduce the impact of extreme rainfall changes [2].

The impact that extreme rainfall changes can have is often detrimental. High heavy rainfall can potentially cause disasters such as floods and landslides; However, on the other hand, if rainfall is low, it can trigger drought and disrupt food availability. High rainfall can also have a big impact on the lives of farmers, fishermen, and also those involved in the world of tourism [3]. Central Maluku Regency is one of the regions that has an erratic rainfall pattern, influenced by geographical conditions [4]. Therefore, efforts to accurately predict rainfall are crucial in risk mitigation-based planning and decision-making.

Rainfall data is a series of time-bound data, so it can be used to predict future rainfall through time series data modeling [5]. Where a prediction method is based on the analysis of the relationship pattern between the variable to be predicted and the time variable [6]. Thus, the time series method plays a role in analyzing and identifying patterns from historical data collected sequentially based on time, then used to make projections to obtain predictions in the future [7].

Time series is a collection of data that is observed sequentially over time [8]. Time series modelling and rainfall forecasts have been carried out at several stations in Bogor and show that most of the 12 stations in Bogor during the first to fifth periods, show that the results of these time series predictions are closer to the actual data [5].

Type Autoregressive Moving Average (ARMA) has been used extensively in various fields to forecast time series data. A study used the ARMA model to predict monthly rainfall in Manado City based on data from 2018–2023. The results showed that the ARMA(1,11) model gave the best results with a MAPE value of 56%, although the accuracy level was moderate. This shows that the ARMA model can provide an overview of trends even though the predictions have limitations in accuracy [1].

Meanwhile, the ARMA model is also applied in a socio-economic context to predict the development prospects of rural areas in Romania. This study emphasizes that the ARMA model is useful in understanding the direction of demographic trends and the factors that affect rural populations, although it is not capable of producing absolute predictive values. The results of the model provide strategic insights for rural development policy making that is more adaptive to potential depopulation [9]. And in the context of renewable energy, the ARMA model has been applied to short-term forecasting of wind power electricity. The results of the study show that the ARMA model is able to capture fluctuating characteristics and uncertainties in wind energy generation data, and can be integrated in the power grid load control system for power supply optimization [10]. In addition to ARMA, several forecasting methods have also been developed and applied in rainfall prediction studies.

In addition to the ARMA model, various forecasting methods have also been applied in rainfall prediction studies, such as SARIMA, Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM). These methods are capable of capturing seasonal patterns and nonlinear relationships in climate data, but generally require larger datasets and more complex computational processes. Several studies in tropical regions of Indonesia have shown that time series and hybrid methods can be used to predict rainfall with varying levels of accuracy depending on the characteristics of the data and the study area [4].

The ARMA model has several advantages because it is relatively simple, easy to interpret, and computationally efficient for modeling stationary time series data. In addition, ARMA is capable of capturing short-term dependency patterns in rainfall data, making it widely used in climatology and hydrology studies. The application of the ARMA model for rainfall prediction in Manado showed that the model was able to describe rainfall patterns, although the forecasting accuracy was still considered moderate [1]. Therefore, the ARMA model was selected in this study because it is suitable for the characteristics of rainfall data in Central Maluku Regency, which satisfied the stationarity assumption, and it provides an effective approach for short-term rainfall forecasting.

The purpose of the research is to find out the results obtained from rainfall prediction in Central Maluku Regency using the ARMA method, the ARMA model used for rainfall prediction in Central Maluku Regency, and the accuracy level of the ARMA model used to predict rainfall in Central Maluku Regency. These results provide important information to support climate data-driven decision-making in the archipelago.

2. RESEARCH METHODS

2.1. Data Source

The data used in this study is secondary data, obtained from the Central Statistics Agency (BPS) of Central Maluku Regency. The data is in the form of monthly rainfall data collected from weather observation stations in the Central Maluku region, namely Amahai station during the last 5-6 years (January 2019 – October 2024), where the data in the forecast period is January 2019 – December 2023 with the data being compared, namely January 2024 – October 2024. Data was collected through a documentation study method, namely by accessing the official publication from the BPS website, titled "Central Maluku Regency in Figures" for years 2020 to 2025.

2.2. Forecasting

Forecasting is the process of describing potential future events by utilizing historical and current data. The purpose of forecasting is to estimate situations that are likely to occur in the future. Data from previous periods and current conditions can be processed into valuable analytical insights to project future events, thereby supporting optimal decision-making [11]. In time series analysis, various data patterns may emerge. These patterns include:

1. Horizontal pattern, occurring when data fluctuates around a constant or stationary average. This pattern is generally random and triggered by unpredictable events.
2. Seasonal pattern, arising when the data series is influenced by seasonal factors or exhibits a pattern that can be anticipated at specific time intervals. This pattern is commonly observed in data related to seasons or certain periods within a year.
3. Cyclical pattern, observed when data experiences annual fluctuations due to long-term economic changes or business cycles. The duration of these changes is typically longer than that of seasonal patterns, with fluctuations influenced by larger-scale economic or political cycles.
4. Trend pattern, occurring when data consistently shows an upward or downward trajectory over the long term. This pattern reflects systematic shifts that may be

driven by technological advancements, changes in consumer behavior, or sustained economic growth.

There are various methods available for forecasting a phenomenon under specific conditions. The choice of an appropriate method greatly influences the accuracy of the forecasting results. An ideal forecasting method is one that can minimize prediction errors as much as possible.

2.3. Autoregressive Moving Average (ARMA)

Selecting the right time series model according to the data will increase the accuracy of predictions. Each model has unique characteristics, so based on those characteristics it can be used as a guide to determine the model that matches the data. Some of the time series models are Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) [12]. The ARMA (Autoregressive Moving Average) model of order (p) and (q) is a time series process formed by the combination of AR(p) and MA(q), which is denoted by Equation (1) as follows:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \qquad (1)$$

where Y_t represents the data at time period t, ϕ_0 is the mean model constant, $\phi_1 y_{t-1}, \phi_2 y_{t-2}, \ldots, \phi_p y_{t-p}$ are past observations from time $t-1$ to ke-$t-q$ that form the Autoregressive (AR) component with coefficients $\phi_{1,}\phi_{2,} \ldots, \phi_p$ and e_t is the error (residual) at time t, while $e_{t-1}, e_{t-2}, \ldots, e_{t-q}$ are errors from previous periods $t-1$ to $t-q$ that form the Moving Average (MA) component with coefficients $\theta_{1,}\theta_{2,} \ldots, \theta_p$.

2.4. Data Analysis

The stages in predicting rainfall in Central Maluku Regency City in the November 2024 – December 2025 period using the ARMA method are [13]:

1. Identify patterns from rainfall data.
2. Testing stationary against Mean using Unit Root Test Augmented Dickey-Fuller (ADF) [14], and stationary to variance using the Box-Cox transformation.
   If the data is not stationary to Mean, will be processed Differenting. Meanwhile, if it is not stationary to variance, it is necessary to transform the data with the Box-Cox until the data is stationary [15], [16]. Transformation Box-Cox is a single-rank data transformation λ. Transformation Box-Cox expressed by the following equation [17].

$$T(Y_t) = \frac{{Y_t}^{\lambda} - 1}{\lambda} \qquad (2)$$

   where, ${Y_t}^{\lambda}$ represents the actual data Y_t raised to the power of the transformation parameter λ, in order to alter the shape of the data distribution to better approximate normality. The value of the transformation form generally used is as specified by the transformation rules [18].

3. Identify ARMA models based on ACF plots and PACF data after stationary.
   A commonly used method for model selection is through a corroboration or plot Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) [19]. Model selection using ACF and PACF can be done graphically by following certain patterns. In the AR(p) model, the ACF pattern tends to decrease gradually or undulatingly, whereas the PACF pattern shows a drastic decrease at a given p-lag (Cut off). In contrast, in the MA(q) model, the ACF pattern shows a drastic

decrease at a given q-length lag (Cut off), while the PACF pattern decreases gradually or undulatingly. Meanwhile, for the ARMA(p,q) model, both the ACF and PACF patterns showed a gradual or undulating decline.

4. Parameter estimation and parameter significance from the ARMA model obtained. Model Autoregressive Moving Average (ARMA) is good at describing an event is a model in which one of them shows that the estimation of the parameters is significantly different from zero [20]. Once the estimated value of each parameter is obtained, the next step is to test the significance of the parameters to determine whether the model is feasible to use or not. One of the methods for estimating the parameters of the ARMA model is the Estimation method Maximum Likelihood (MLE).
5. Residual diagnostic test of the ARMA model.
   Residual diagnostic testing is a process of testing the feasibility of the model. In the selection of the best ARMA model, it must also have a residual model that is normally distributed and the residual is not correlated with each other or White noise. White noise assume no correlation in the residual series performed using the Ljung-Box Test [17]. Meanwhile, the normality assumption test aims to test the normal distribution of residual which can be tested using the Kolmogrov-Smirnov Test.
6. Calculate MAPE values to find out the prediction accuracy value.
   One of the measuring tools that can be used to measure the accuracy level of the model is Mean Absolute Percentage Error (MAPE). MAPE indicates the magnitude of the error in forecasting compared to the actual value [21]. MAPE is obtained as follows:

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} \tag{3}$$

   where n is the number of data points, and Y_t is the actual observation data at time t, while $\hat{Y}_t$ is the predicted data at time t.

   The criteria for calculating the MAPE value used are presented in the Table as follows [22].

Table 1. MAPE Criteria

Value MAPE (%)	**Criterion**
MAPE < 10	Highly Accurate
10 ≤ MAPE < 20	Accurate
20 ≤ MAPE < 50	Quite Accurate
MAPE ≥ 50	Bad

   The smaller the MAPE value produced, the better the prediction model used.
7. Perform predictions using the best ARMA model.

3. RESULTS AND DISCUSSION

The data characteristics from the visualization results in **Figure 1** are patterns of monthly rainfall data in Central Maluku Regency in the period January 2019 – December 2023.

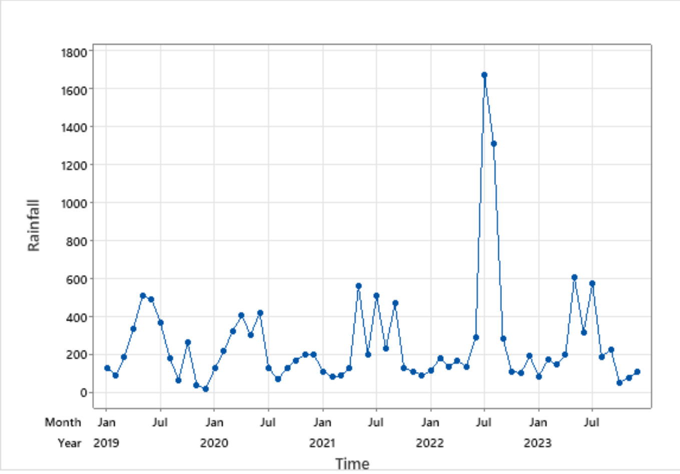


Figure 1. Rainfall Data Plot

Based on **Figure 1**, it can be seen that Rainfall data has a stationary pattern because Rainfall data revolves around the mean value of Rainfall data in Central Maluku Regency in the period January 2019 – December 2023. However, data stationary cannot be determined based solely on visualization. It is necessary to carry out a data stationary test which includes a stationariness test on variance and on mean.

Table 2. Box-Cox Transform Test

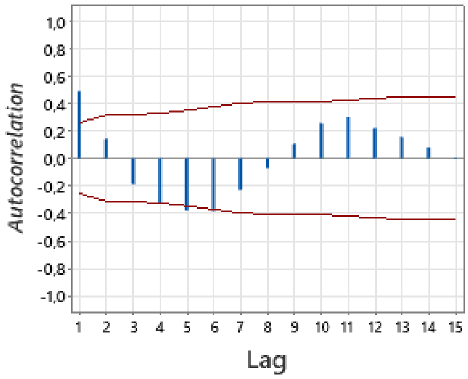
Data		Value λ	Stationary
Rainfall	Before the Transformation	0	Not
	After the Transformation	1	Yes

Based on **Table 2**, a value of $\lambda \neq 1$ was obtained, indicating that the rainfall data is not yet stationary in variance, and therefore a transformation process was carried out. After performing the transformation once, a value of $\lambda = 1$ was obtained. This means that the transformed rainfall data is already stationary in variance. The next step is to test the stationarity of the data with respect to the mean, the results of which are presented in **Table 3** below.

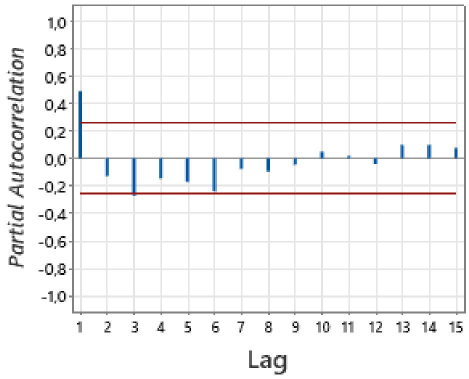
Table 3. ADF Test

Data	ADF Value	$p - value$
Rainfall Transformation	- 5.017	0.000

Based on **Table 3**, the $p - value$ of 0.000 was obtained. In the ADF test, it is stated that if the p-value < α, then the data is stationary with respect to the mean. According to this criterion, the p-value = 0.000 < α = 0.05. This means that the transformed rainfall data is already stationary with respect to the mean. The process will then continue by identifying the model using a correlogram or ACF and PACF plots, which can be seen in **Figure 2**.



(a)



(b)

Figure 2. Plot (a) of ACF dan (b) PACF

Based on **Figure 2**, it can be assumed that several models were formed. In the ACF plot, the orders MA(0) and MA(1) are obtained because the cut-off after the 1st lag. Meanwhile, in the PACF plot, the AR(0) and AR(1) orders are obtained because they are also cut off after the 1st lag. So that the possible ARMA models are presented in **Table 4** as follows.

Table 4. Model Identification

Data	Model ARMA (p,q)
Rainfall	ARMA(1,0)
	ARMA(0,1)
	ARMA(1,1)

After that, an estimation and significance test of the parameters of each temporary model that has been formed previously will be carried out, and the results as presented in **Table 5** will be obtained.

Table 5. Parameter Significance Estimation and Test

Type	Parameters	Coefficient	$p-value$	Significant
ARMA $(\mathbf{1},\mathbf{0})$	AR (1)	0.496	0.000	Yes
ARMA $(\mathbf{0},\mathbf{1})$	MA (1)	-0.424	0.001	Yes
ARMA $(\mathbf{1},\mathbf{1})$	AR (1)	0.404	0.101	Not
	MA (1)	-0.124	0.637	Not

Based on **Table 5**, it is known that there are two models in which each parameter is significant, and these will proceed to the residual diagnostic test, namely the ARMA(1,0) and ARMA(0,1) models.

Table 6. White Noise Test

Type	Lag	$\chi^2_{calculated}$	p-value	White Noise
ARMA (1,0)	12	15.07	0.129	Yes
	24	21.58	0.485	Yes
	36	31.98	0.567	Yes
	48	58.86	0.097	Yes
ARMA (0,1)	12	26.19	0.003	Not
	24	36.45	0.027	Not
	36	50.82	0.032	Not
	48	85.03	0.000	Not

Based on **Table 6**, it can be seen that the model that meets the criteria of the white noise residual diagnostic test is the ARMA(1,0) model, with p-value for each lag > $\boldsymbol{\alpha}$ = 0.05. This model will proceed to the next diagnostic test, which is the normality test of the residuals.

Table 7. Kolmogorov-Smirnov Test

Model	$D_{calculated}$	$p-value$
ARMA (1,0)	0.064	> 0.150

Based on **Table 7**, it is known that the residuals of the ARMA(1,0) model are normally distributed because the p-value > α = 0,05. The ARMA(1,0) model was selected as the best model because it met all model adequacy criteria. The AR parameter was statistically significant, and the residuals satisfied the white noise and normality assumptions. In contrast, the ARMA(0,1) model failed the white noise test, indicating that the model could not fully capture the dependency pattern in the rainfall data. Meanwhile, the ARMA(1,1) model was not selected because its parameters were not statistically significant. These results indicate that the rainfall data in Central Maluku Regency are more strongly influenced by autoregressive components from previous observations.

Therefore, the next step is to calculate the MAPE value to assess how accurate the model is.

Table 8. MAPE Values

Predictions	Type	MAPE Values	Information
Rainfall	ARMA (1,0)	43.24%	Quite Accurate

Based on **Table 8**, the MAPE value is 43.24% for the ARMA(1,0) model, which indicates that the model is reasonably accurate for predicting rainfall. The MAPE value of 43.24% indicates that the ARMA(1,0) model is categorized as reasonably accurate. In rainfall forecasting studies, a MAPE value below 50% is generally considered acceptable due to the high fluctuation and uncertainty of rainfall data. Compared to a previous study in Manado City that produced a MAPE value of 56% **[1]**, the model in this study shows better forecasting accuracy. The next step is to forecast rainfall using the ARMA(1,0) model in Central Maluku Regency for the period of November 2024 to December 2025, as presented in **Table 9** below.

Table 9. Prediction Results

Period		Prediction Results
Year	**Month**	**Rainfall (mm)**
2025	November	180.45654481
	December	180.46195859
2026	January	180.46556789
	February	180.46556788
	March	180.46737259
	April	180.46737259
	May	180.46737255
	June	180.46737258
	July	180.46737256
	August	180.46737261
	September	180.46737263
	October	180.46737263
	November	180.46737263
	December	180.46737263

Visualization of the results of rainfall prediction in Central Maluku Regency in the period November 2024 – December 2025 can be seen in **Figure 3**.

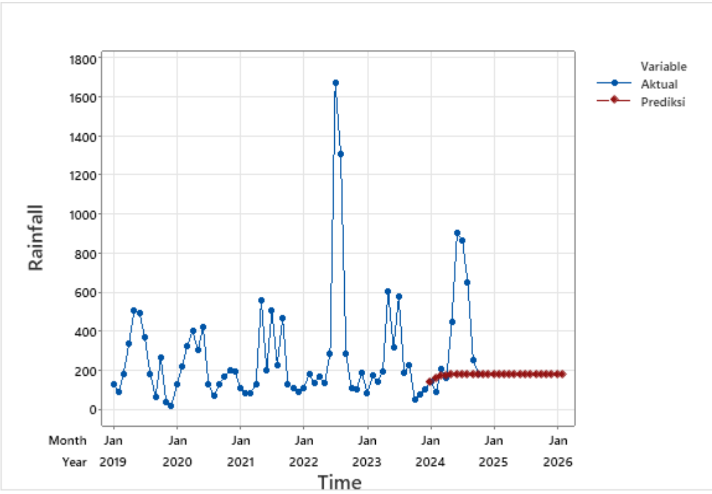


Figure 3. Visualization of Rainfall Prediction Results in Central Maluku Regency for the period of November 2024 – December 2025

Based on the prediction results, rainfall in Central Maluku Regency for the next 14 months shows a much more stable and lower pattern, with values consistently hovering around 200 mm or less each month. This indicates a significant decrease in the expected rainfall compared to previous historical patterns, which tended to be unstable and subject to large variations. These findings are consistent with previous studies showing that ARMA-based forecasting models tend to produce more stable prediction patterns compared to historical rainfall fluctuations [1]. This occurs because the model captures the general trend and dependency pattern in the data while minimizing random fluctuations. The predicted decrease in rainfall may also indicate the influence of climate variability in tropical regions.

4. CONCLUSION

The study showed that the ARMA(1,0) model could be used to predict rainfall in Central Maluku Regency for the period November 2024 to December 2025, with a MAPE value of 43.24%, which is categorized as reasonably accurate. The prediction results indicate a decreasing rainfall trend that may affect important sectors such as agriculture, fisheries, and water resource availability. Therefore, the findings of this study can support local governments and stakeholders in developing climate adaptation strategies, water resource management planning, and drought risk mitigation efforts.

In addition, the forecasting results may serve as supporting information for decision-making related to agricultural planting schedules, water distribution management, and disaster preparedness in Central Maluku Regency. For future research, prediction accuracy could be improved by incorporating additional climate variables such as temperature, humidity, wind speed, and sea surface conditions, as well as by applying hybrid or machine learning-based forecasting methods to better capture complex climate patterns.

Funding Information

Authors state no funding involved.

Author Contributions Statement

Table 10. **Author Contributions**

Name of Author	C	M	So	Va	Fo	R	D	O	E	Vi	Su	P
Indri Kezia Latupeirissa	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
Fadila Rumbaroa		✓			✓			✓				
Wa Ode Ma'arifah		✓			✓					✓		
Jean Apituley	✓					✓				✓		
Sahrul Rumalean	✓					✓				✓		
Henry Junus Wattimanela											✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration

Conflict of Interest Statement

Authors state no conflict of interest.

Data Availability

The data supporting the findings of this study were obtained from the official publications of the BPS of Central Maluku Regency, titled " Central Maluku Regency in Figures" for the years 2020 to 2025. These publications are publicly available and can be accessed through the official website of BPS Central Maluku at: https://malukutengahkab.bps.go.id.

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