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Comparison of The Singular Spectrum Analysis and SARIMA for Forecasting Rainfall in Padang Panjang City*

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Abstract

Indonesia is an area with a tropical climate, so it has two seasons, namely the rainy season and the dry season. The rainy season lasts from November to March and during this period rainfall tends to be high in several areas. Padang Panjang City is one of the cities with the smallest area in West Sumatra Province, which has the nickname Rain City. This is because the city of Padang Panjang has cool air with a maximum air temperature of 26.1 °C and a minimum of 21.8 °C, so this city has a fairly high level of rainfall with an average of 300 to 400 mm/year. This article discusses rainfall forecasting for Padang Panjang City by comparing the Singular Spectrum Analysis and Seasonal Autoregressive Integrated Moving Average methods. The data used spans 8 years, from January 2016 to December 2023. Forecasting results are obtained from the best method selected based on the smallest Mean Absolute Percentage Error value. The Singular Spectrum Analysis method has a Mean Absolute Percentage Error value of 5.59% and Singular Spectrum Analysis and Seasonal Autoregressive Integrated Moving Average $(1,0,1)(0,1,1)^{12}$ has a value 7.43%. The best forecasting method is obtained by the Singular Spectrum Analysis method.

Keywords: SSA, SARIMA, MAPE

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1. Introduction

Rainfall is the amount of water that falls on a flat ground surface within a certain period of time which is measured in millimeters (mm) above a horizontal surface. One millimeter of rainfall means that on a flat area of 1 m^2 there will be 1 mm of water or 1 liter. Rainfall can be influenced by local factors such as topography (Tresnawati & Rosyidah, 2019). Areas around mountains or coasts usually experience high rainfall because water vapor easily collects and forms rain clouds. On the other hand, areas that are far from sources of water vapor or blocked by mountains often experience lower rainfall.

One area in Indonesia that has high rainfall is Padang Panjang City. Padang Panjang City is one of the cities with the smallest area in West Sumatra Province, known as the City of Rain. According to the Information and Documentation Management Officer (PPID) of Padang Panjang City, this nickname was given because the city is located in an altitude area which is between 650 and 850 meters above sea level. Apart from that, Padang Panjang City is located in a mountainous area and is flanked by three large mountains: Mount Marapi, Mount Singgalang and Mount Tandikat. This geographical condition causes Padang Panjang City to have cool air, with a maximum air temperature of 26.1 °C and a minimum of 21.8 °C so that Padang Panjang City has quite high levels of rainfall with an average of 300 to 400 mm/year.

The high rainfall in Padang Panjang City has a significant impact on the agricultural sector, which is one of the main sectors that supports the economy of the local community. According to the Regional Medium Term Development Plan (RPJMD) of Padang Panjang City, most of the land in this area is dominated by agricultural land with an area of 1,428 hectares. Therefore, the availability of water from rainfall is an important factor for the success of agricultural production. High rainfall in Padang Panjang City can significantly affect harvest success and planting schedules. For this reason, accurate rainfall forecasting is needed to help farmers determine the right time to plant and harvest, as well as anticipate the risk of crop failure due to extreme weather conditions.

Based on data from the Padang Panjang City Central Statistics Agency, the highest rainfall in Padang Panjang City was in June 2021 with a figure of 789.9 mm, while the lowest rainfall occurred in July 2016, namely 96.4 mm. Monthly rainfall data in Padang Panjang City for the period January 2016 to December 2023 is presented in Figure 1.

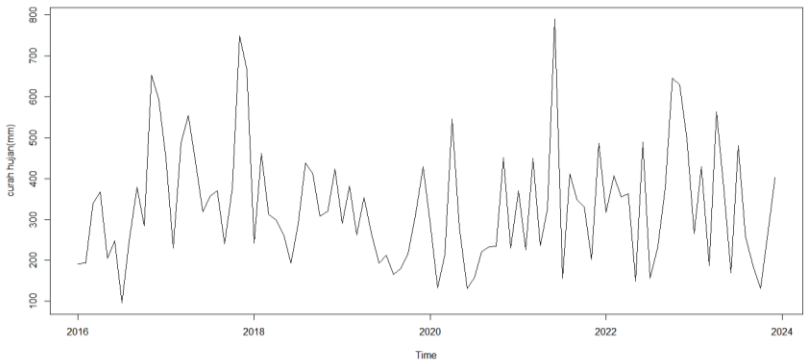


Figure 1: Padang Panjang City Rainfall Plot 2016 – 2023

From Figure 1, the monthly rainfall pattern in Padang Panjang City for the period January 2016 to December 2023 shows a seasonal pattern. Where this data shows quite significant fluctuations from month to month with rainfall patterns tending to increase or decrease in certain periods consistently every year. Padang Panjang City experiences peak rainfall every year exceeding 400 mm.

Forecasting is a technique used to estimate the value of an event in the future. This is in accordance with opinion (Makridakis et al., 1997) which states that forecasting is an important tool in planning to make it more effective and efficient. By looking at the seasonal patterns in monthly rainfall data in Padang Panjang City, forecasting using the Singular Spectrum Analysis (SSA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) methods can be used to analyze and predict rainfall patterns more accurately.

The SSA method is a technique for analyzing and forecasting time series data that is current and powerful in combining analyzes such as time series, multivariate statistics, multivariate geometric, dynamical systems, and signal processing (Jatmiko et al., 2017). SSA aims to decompose the original series into a small number of components/groups that can be distinguished such as slow trends, moving components and unstructured noise (Idrus et al., 2022). Apart from that, the SARIMA method is a forecasting method used for data that contains seasonal elements. SARIMA is a development of the ARIMA (Autoregressive Integrated Moving Average) model which combines seasonal elements into the analysis. This model consists of several components: autoregressive (AR), moving average (MA), and differencing (I), all of which can be considered in a seasonal context (Alwi et al., 2021).

Several previous studies regarding forecasting using the SSA and SARIMA methods include, Purnama (2022) conducted research on rainfall forecasting in Gorontalo Province using the SSA method. Based on the research carried out, the best window length (L) value was 36 with a Mean Absolute Percentage Error (MAPE) value of 2.9%, which shows that the SSA method can be used to predict rainfall in Gorontalo Province. Furthermore D. I. Purnama (2021) also conducted research on rainfall forecasting in Parigi Moutong Regency using the SARIMA model. Based on research conducted by the best Sarima model, namely $(1,1,0)$ $(0,1,1)^{12}$ with a MAPE value of 12.0157 on training data and 16.4647 on testing data. Further research is regarding the comparison of the SSA method and SARIMA carried out by Fitri et al., (2021) in predicting rainfall in West Sumatra. Based on research conducted, the MAPE value for SSA is 17% and the MAPE for SARIMA is 22.75%. From research Fitri et al.,(2021) concluded that the two methods have very different approaches, so that the models cannot be formally compared. However, for real-world time series for which the model is unknown, SARIMA and SSA can be compared numerically.

Based on the description above, the author conducted comparative research on the Singular Spectrum Analysis (SSA) method and the Seasonal Autoregressive Integrated Moving Average (SARIMA) method in predicting rainfall in Padang Panjang City. The difference between this study and previous research lies in the data used; this study uses data from Padang Panjang City, consisting of 96 data points.

2. Methodology

2.1 Types of Research

This research is applied research which aims to provide solutions and solve a problem. The research carried out was the application of the SSA and SARIMA methods in predicting rainfall in Padang Panjang City.

2.2 Data Types and Sources

The data used is secondary data. The data obtained came from the Padang Panjang City Central Statistics Agency website. The data used is Padang Panjang City rainfall data from January 2016 to December 2023.

2.3 Data Analysis Techniques

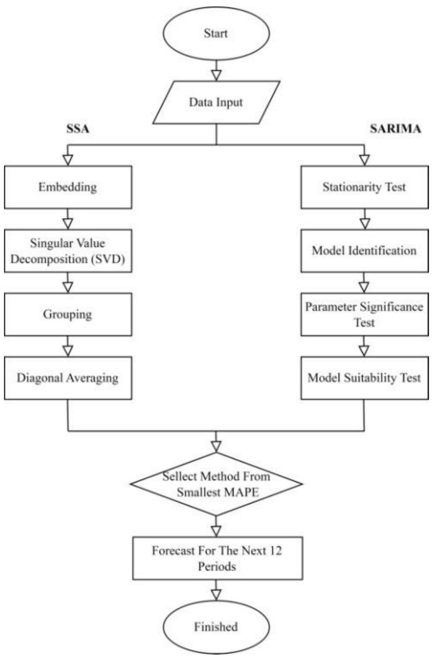


Figure 2: Flowchart SSA and SARIMA

Based on Figure 2, the analysis stages of this study are as follows:

1) Input the data to be analyzed, namely the rainfall data of Padang Panjang City from January 2016 to December 2023.
2) The application of Singular Spectrum Analysis
   a. Embedding
   In the embedding stage, the data is converted into multidimensional data known as the trajectory matrix X, with the order $L \times K$. The value parameter L (windows length) is one of the important parameters in SSA. The selection range for the L value is 2 < L < N/2, where N is the amount of data. The path matrix X formed is also called the Hankel matrix and is expressed in the following form (Idrus et al., 2022):
   $$X = (x_i)_{LXK} = [x_1, x_2, \dots, x_N] = \begin{bmatrix} x_1 & x_2 & \dots & x_K \\ x_2 & x_2 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{bmatrix} \quad (1)$$
   b. Performing Singular Value Decomposition (SVD).
   SDV aims to separate components in the decomposition of time series data. The first step is to form a symmetric matrix S=XXT. Next, using the equation det ($S - \lambda_I$) = 0 we obtain the eigenvalue λ_i = $\lambda 1$,…,λL where $\lambda 1 \geq \cdots \geq \lambda L \geq 0$ and the eigenvector $U_i = U_1, \dots, U_L$ from the matrix S. The singular value matrix is the positive root of the eigenvalue ($\sqrt{\boldsymbol{\lambda i}}$) (Permata et al., 2023).
   c. Grouping
   Carry out Grouping to group the components of trend, seasonality and noise, and look at the wcorrelation plot graph to see the separation between. Grouping is carried out, which is the stage of eigentriple grouping based on certain characteristics possessed by each component. Grouping is done by grouping the index set i = {1,2,…,d} into m disjoint subsets $I_1, I_2, \dots, I_M$ with m = d. Next, X_i is adjusted to group I (Wicaksono et al., 2019).
   d. Diagonal averaging
   Diagonal Averaging is the final stage in SSA. In this stage, reconstruction is performed for each matrix in matrix X to create a new time series data with length N, Let $Y = L \times K$ (E. Purnama, 2022).
3) The application of SARIMA
   a. Data stationarity testing
   Stationarity testing is performed on the variance and mean values. Stationarity for variance is tested using the Box–Cox Transformation method, where the data is considered stationary for variance if the Rounded Value obtained is 1.00 (Yulistia et al., 2021). Meanwhile, stationarity for the mean is checked by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots (Fadliani et al., 2021).
   b. Model Identification
   SARIMA is a development of the ARIMA method for seasonal patterns, for example quarterly, monthly and annual data (Prianda & Widodo, 2021). The SARIMA method consists of two components, namely non-seasonal with the p, d, q model and seasonal with the P, D, Q and also S models, so the notation for SARIMA that is formed is (Susanti et al., 2024):

$$(p, d, q)(P, D, Q)^S \tag{2}$$

Information:

p : *Autoregressive* non-seasonal

q : *Moving Avarage* non- seasonal

d : *Differencing* non- seasonal

P : *Autoregressive* seasonal

Q : *Moving Avarage* seasonal

D : *Differencing* seasonal

S : Period for seasonal

c. Parameter Significance Model
The significance test of model parameters is used to determine whether the parameters obtained are suitable to be included in the model (Fahmuddin & Mustika, 2023). This test can be performed by formulating hypotheses:
H_0 : $\hat{\theta} = 0$ (The parameter in the model is significant)
H_0 : $\hat{\theta} \neq 0$ (The parameter in the model is not significant).
The rejection region for this parameter significance test is determined using the p-value, where H_0 is rejected if the p-value < α $(0{,}05)$.

d. Model Suitability Test
The model suitability test consists of the white noise assumption test and the residual normality test (Sari et al., 2018). The residual normality test uses the Kolmogorov-Smirnov test statistic by formulating the following hypothesis:
H_0 = normally distributed.
H_1 = not normally distributed.
The decision rule is to accept H_0 if the $p - value \geq \alpha$, and to reject H_0 if the $p - value < \alpha$ (0.05) (Quraisy, 2022).

The white noise assumption test uses the Ljung-Box test statistic with the following hypotheses:
H_0 = The residual meets the white noise condition
H_1 = The residual does not meet the white noise condition.
The decision for the white noise test if the $p - value > \alpha$ (0.05) (Fortuna & Oktaviarina, 2024).

4) Calculate the comparison of the SSA and SARIMA methods
Compare the SSA and SARIMA values based on the forecasting accuracy measure (MAPE). The best method is chosen based on the smallest MAPE value.

5) Forecast for the next 12 months using the best method.

3. Results and Discussion

3.1 Singular Spectrum Analysis Method

Embedding

The embedding stage is the stage where the initial data in the form of one dimension is converted into data in a multidimensional form. This is done by forming a trajectory matrix with dimensions $L\,X\,K$ (Fadhilah Fitri et al., 2017). In this study the window length (L value) used was 36 which was obtained from the results of trial and error. So the value $K = N - L + 1 = 96 - 36 + 1 = 61$.. The shape of the trajectory matrix is as follows:

$$X = (x_i)_{36X61} = [x_1, x_2, \dots, x_{96}] = \begin{bmatrix} 192{,}4 & 193{,}5 & \cdots & 235{,}7 \\ 193{,}5 & 338{,}8 & \cdots & 325{,}6 \\ \vdots & \vdots & \ddots & \vdots \\ 413{,}4 & 307{,}7 & \cdots & 402{,}6 \end{bmatrix}$$

Singular Value Decomposition (SVD)

The trajectory matrix formed is then used in Singular Value Decomposition (SVD). In the SVD stage, eigentriple components will be generated. The eigentriple component consists of a singular value, eigenvector, and principal component (F. Fitri et al., 2020). Visually, the singular value is displayed as shown in Figure

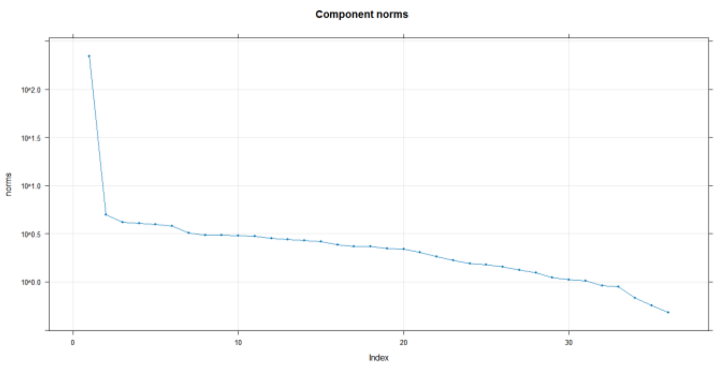


Figure 3: Plot Singular Value

In the figure, the vertical axis is a singular value, while the horizontal axis is an index with a length equal to the value of L. Based on Figure 3, it can be seen that the first singular value has a higher value compared to the other singular values. This indicates that the first singular value can be identified as a signal component. The eigenvector value can be described as:

Figure 4: Plot Eigenvector

Figure 4 is a plot of eigenvector 1 to eigenvector 36. Looking at the eigenvector plot can help in grouping components, including trend, seasonal and noise components.

Grouping

At the reconstruction stage, a stage is carried out, namely grouping. Determination of grouping in SSA is carried out by trial and error. Determining grouping can be helped based on eigenvector plots to see the components of seasonal groups and noise groups. Determining these components is subjective to the researcher. Good grouping, if there is no correlation between the groups formed.

A trend is a slowly varying component of a time series that does not contain an oscillatory component. Therefore, to determine the trend in a time series, it can be seen based on singular values that vary slowly. In Figure 4, it can be seen that eigenvector 1 has a trend pattern so that eigentriple 1 can be grouped as a trend component. Eigenvector 2 to eigenvector 29 have irregular patterns so that grouping seasonal components will be done by trial and error. Trial and error is presented in the table.

Table 1: Trial and Error Grouping

Grouping	MAPE
Trend=c(1),Season1=c(2,3,4,5,6),Season2=c(7:13),Season3=c(14:23)	5,7533
Trend=c(1),Season1=c(2,3,4,5,6),Season2=c(7:13),Season3=c(14:19)	5,6419
Trend=c(1),Season1=c(2,3,4,5,6),Season2=c(7:13),Season3=c(14:19), Season4=c(24:29)	5,5989
Trend=c(1),Season1=c(2,3,4,5,6),Season2=c(7:13),Season3=c(14:31)	6,0075
Trend=c(1),Season1=c(2,3,4,5,6),Season2=c(7:13),Season3=c(14:29)	5,8476

Based on the results of trial and error ini Table 1, the selected grouping are 5 groups, namely trend, seasonal 1, seasonal 2, seasonal 3, and seasonal 4. The trend group consists of eigentriple 1. Seasonal group 1 consists of eigentriple 2,3,4,5,6. Seasonal group 2 consists of eigentriple 7 to 13. Seasonal group 3 consists of eigentriple 14 to

19. And seasonal group 4 consists of eigentriple 24 to 29. A good grouping is if each group is mutually exclusive. This can be seen based on the w-correlation graph.

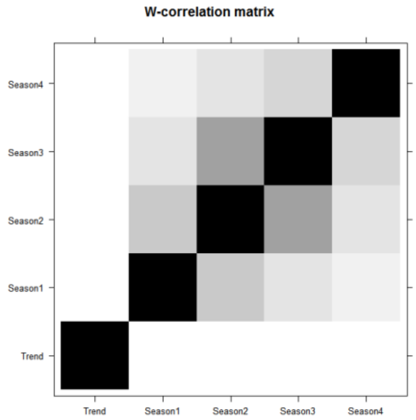


Figure 5 : Plot w-correlation

Based on Figure 5, it can be concluded that the first group, namely trend, has no correlation with the seasonal group. It can be seen that the components have good separation. Furthermore, seasonal 1 with seasonal 2, seasonal 3, and seasonal 4 have a correlation. From Figure 5 it can be concluded that each group is mutually exclusive. A good grouping is if each group is mutually exclusive.

Diagonal Averaging

After the clustering is formed, the next step is to perform diagonal averaging. The purpose of diagonal averaging is to create a new series based on the formed clustering. The results of the diagonal averaging obtained are shown in the Table 2.

Table 2:Diagonal Averaging

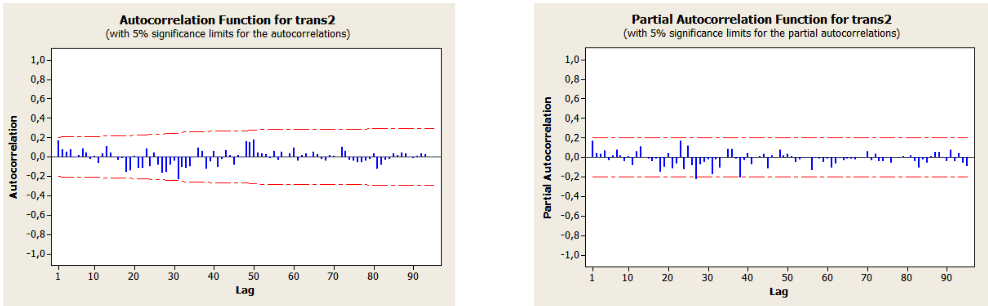
Data	Trend	Seasonal 1	Seasonal 2	Seasonal 3	Seasonal 4	Diagonal Averaging
192,4	5.8913	-0.2864	-0.4414	-0.0703	0.0373	5.1305
193,5	5.8990	-0.4511	-0.2088	-0.0703	-0.0416	5.2906
⋮						⋮
148,8	5.5364	0.1282	-0.3553	-0.1721	-0.0372	5.0999

3.2 SARIMA Method

Identifying stationarity in the variance seen from the Box–Cox Transformation In carrying out this identification, the data is considered stationary for variance if the Rounded Value obtained is 1.00. After the data transformation has been carried out twice, the data is stationary regarding variance because the lambda value or Rounded Value is already 1.00.

Identify stationarity for the average, through checking the ACF and PACF plots.

Non – Seasonal

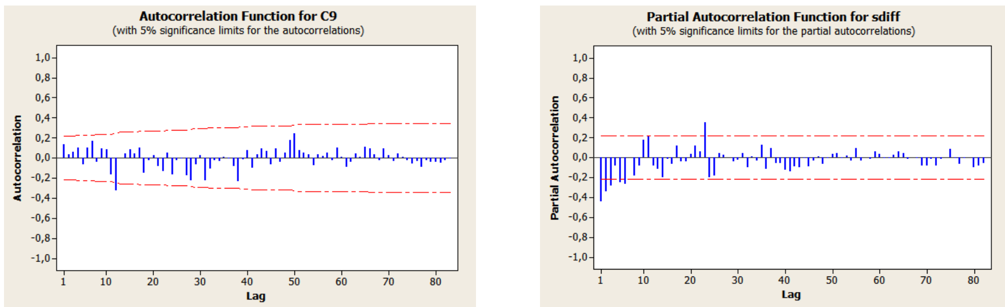


(a) (b)

Figure 6: (a) Plot ACF Non – Seasonal, (b) Plot PACF Non – Seasonal

Based on the non-seasonal ACF and PACF plots, the ACF plot with no lag is outside the confidence interval line, and the 1 lag PACF plot is outside the confidence interval line, both of which are no more than 3 so that the data is stationary about the mean. So it can be concluded that in PACF 1 lag comes out, so p = 1, where in the ACF graph also 0 lag comes out, q = 0. And no differencing is done on non-seasonal data, so d=0. Next, because the data is seasonal, differencing is carried out. Differencing is carried out for the 12th lag because the data period used is annual.

Seasonal



(a) (b)

Figure 7: (a) Plot ACF Seasonal, (b) Plot PACF Seasonal

Based on the seasonal ACF and PACF Plots, the ACF Plot with 1 seasonal lag comes out of the confidence interval, namely at lag 12, while in the PACF Plot there is no seasonal lag out, so it can be concluded that P = 0 and Q = 1. Because the data is seasonal, differencing is carried out. Differentiating is carried out for the 12th lag because the data period used is annual so D=1. From the results of the ACF and PACF non-seasonal/seasonal Average Temperature data for Padang Panjang City, the temporary model estimate $(p, d, q)(P, D, Q)^s$ = $(1,0,0)(0,1,1)^{12}$. Based on the temporary model obtained, there are eight predicted models. This alleged model will be tested for significance on the parameters, where if the P-value < 0.05 it is declared significant. Of the several existing estimated models, two models were declared significant, namely the model in the table.

Table 3: Comparison of SARIMA MAPE Values

Model	MAPE
SARIMA $(1,0,1)(0,1,1)^{12}$	7,43
SARIMA $(1,1,0)(0,1,1)^{12}$	8,22

Based on the Table 3, the SARIMA model has a P-Value < 0.05. Then a MAPE test is carried out where the selected MAPE value must be minimum. SARIMA $(1,0,1)(0,1,1)^{12}$ is the one with the smallest MAPE, then the residual normality test assumption and white noise test are tested.

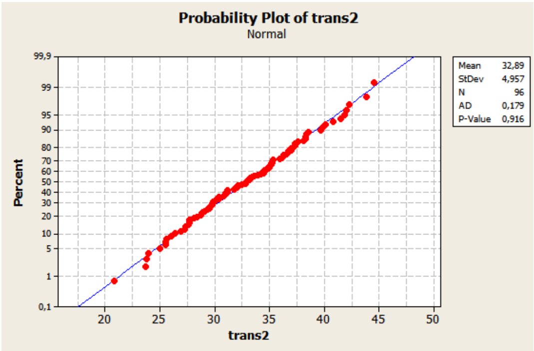


Figure 8: Plot Normality Test

Table 4: White Noise Test

Model	Lag	P-Value	Decision	Conclusion
$(1,0,1)(0,1,1)^{12}$	12	0,438	H_0accepted	*White noise*
	24	0,386	H_0 accepted	*White noise*
	36	0,208	H_0 accepted	*White noise*
	48	0,252	H_0 accepted	*White noise*

From the residual normality test in Figure 8, a p-value of 0.916 was obtained. Since the p-value $> \alpha(0.05)$, $H_0$is accepted, which means the normality assumption for this model is satisfied. Based on the Ljung – Box results on the SARIMA model $(1,0,1)(0,1,1)^{12}$ the p–value obtained is ≥ 0.05 indicating that H_0. This model meets the white noise assumption.

3.3 Comparison of SSA and SARIMA Methods

Table 5: Comparison MAPE SSA and SARIMA

No	Methods	MAPE
1	SSA	5.59
2	SARIMA	7.43

Based on the table above, the MAPE SSA value is 5.59% and the MAPE SARIMA is 7.43%. From these results, the MAPE SSA value is smaller than SARIMA. So the SSA model was chosen as the best model for forecasting because it has the smallest MAPE value. The selected best model can be used to forecast rainfall in Padang Panjang City.

3.4 Forecasting with The Best Model

The best forecasting method is using the SSA method. Therefore, rainfall forecasting for Padang Panjang City is conducted for the next 12 months, from January 2024 to December 2024. Based on the forecasting results shown in Table 6, the highest rainfall in Padang Panjang City from January 2024 to December 2024 is predicted to occur in Mei, with 413.2596 mm of rainfall, while the lowest rainfall is predicted in March, with 209,0582 mm of rainfall. This prediction provides an important overview of the rainfall pattern expected in 2024. With this information, relevant parties can be better prepared to plan disaster mitigation measures or more effective agricultural strategies. The forecasting results can also be used for planning infrastructure that is more adaptive to the changes in climate.

Table 6: Forecasting 12 months

Month	Forecast Data
January 2024	316,4187
February 2024	375,0971
March 2024	209,0582
April 2024	306,5052
Mei 2024	413,2596
June 2024	283,0008
July 2024	306,2164
August 2024	345,3740
September 2024	334,7395
October 2024	213,9332
November 2024	320,4108
December 2024	282,8349

4. Conclusion

In this study, monthly rainfall data in Padang Panjang City from January 2016 to December 2023 was forecasted using two methods, namely Singular Spectrum Analysis (SSA) and SARIMA. These methods employ different approaches to analyze time series data, providing a comprehensive evaluation of rainfall patterns. The results show that the SSA method achieved a MAPE value of 5.59%, while SARIMA $(1,0,1)(0,1,1)^{12}$ obtained a MAPE value of 7.43%. These findings indicate that the SSA method is a superior forecasting approach due to its smaller MAPE value, making it a valuable tool for the community and the government in anticipating rainfall changes in Padang Panjang City.

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