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A COMPARATIVE EVALUATION OF SARIMA AND FUZZY TIME SERIES CHEN MODELS FOR RAINFALL FORECASTING IN MAKASSAR

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ABSTRACT

High rainfall intensity in Makassar often leads to flooding. Therefore, forecasting the amount of rainfall is necessary as a reference for taking appropriate mitigation measures. This study was conducted to select the best model between the SARIMA and Fuzzy Time Series (FTS) Chen based on a comparison of their forecasting accuracy, as well as to forecast the amount of rainfall in Makassar for 2024 using the best model. For this study, monthly rainfall data covering the period from January 2014 to December 2024 were collected from the official website of the Central Statistics Agency (BPS) Makassar. Based on the analysis results, SARIMA(7,2,3)$(1,1,1)^{12}$ *was selected as the best model, with an MAE value of 2.654 and an RMSE value of 3.846. The contribution of this study lies in providing an empirical comparison between SARIMA and FTS Chen for rainfall forecasting in tropical regions. However, the limitation of this study is that the forecasting relies solely on historical rainfall data, without incorporating other meteorological variables that may influence rainfall patterns.*

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1. INTRODUCTION

Indonesia has a tropical climate due to its location along the equator, resulting in high rainfall, including in Makassar. Rainfall is the amount of rainwater accumulated in a flat area that does not flow, absorb, or evaporate and is measured in millimeters or inches. One millimeter of rainfall represents the volume of water over one square meter, which is equivalent to one liter [1]. In Indonesia, the dry season usually runs from May to October, whereas the rainy season extends from November to April. Increased rainfall during the rainy season can trigger hydrometeorological disasters such as landslides and floods [2]. Makassar is classified as a flood-prone area [3]. According to information from www.news.detik.com, the flood that occurred in Makassar on December 26, 2022, was recorded as the most severe of the year [4]. The flood submerged three districts—namely, Manggala, Biringkanaya, and Tamalanrea. Furthermore, a total of 8,687 people were affected by the flood. According to information from the Regional Disaster Management Agency of Makassar, the flood, which reached a height of up to 2 meters, caused severe disruption to public mobility. It also resulted in material losses amounting to billions of rupiah due to 3,046 housing units being submerged. Additionally, 182 flood evacuees suffered from various health problems [4].

In light of this issue, an accurate forecasting method is needed to predict the amount of rainfall over a certain period. This information is essential as a reference for both the public and local government in taking mitigation measures to minimize the risk of flooding. Forecasting involves analyzing historical data to predict future events [5]. Currently, time series analysis is a popular method used in forecasting. Several time series methods frequently applied include ARIMA, SARIMA, Fuzzy Time Series (FTS), and Exponential Smoothing [6], [7], [8]. SARIMA is a modified version of the ARIMA model that incorporates seasonal patterns [9]. The advantage of SARIMA lies in its effectiveness in capturing seasonal patterns and trends through the seasonal components integrated into the model, which are not present in the standard ARIMA model [10], [11], [12]. However, SARIMA requires the data to meet the assumption of stationarity [13]. A study in Nigeria showed that the SARIMA $(2,0,1)(2,1,1)^{12}$ was optimal model based on statistical criteria such as the Box-Pierce residuals test. It was effective in modeling the seasonal rainfall patterns in Nigeria and capable of providing accurate forecasts for the medium to long term [10]. However, this study has a limitation. It only applied the SARIMA model without comparing it to alternative forecasting methods, such as Fuzzy Time Series, so it is unclear whether other methods could provide higher accuracy for data with complex seasonal patterns.

The FTS method offers a solution to this limitation by using fuzzy sets to map data without the need to satisfy assumptions such as stationarity, normality, or homoscedasticity [13], [14]. Moreover, FTS is capable of capturing the complexity and uncertainty inherent in rainfall data, which often exhibit irregular patterns [15]. However, the accuracy of FTS depends on the number of classes and the length of intervals defined at the outset [16]. Several FTS models include those proposed by Song-Chissom *et al.* [17]. The Chen model is chosen in this study because Chen's method provides better short-term forecasting accuracy, can handle variability in rainfall more robustly, and has a simple computational process, making it easier to implement compared to other Fuzzy Time Series models [18]. A study in Medan found that the Chen model outperformed others in forecasting monthly rainfall, achieving a lower MAPE value of 8.002% compared to the Cheng model and the Markov Chain [19]. However, this study also has several limitations. It was conducted only in Medan, so the results may not be directly generalizable to other regions with different rainfall patterns. The comparison was limited to FTS variants and did not include classical time series models such as SARIMA, leaving uncertainty about the relative performance of Chen's model against these methods.

According to the previous explanation, a research gap remains regarding the comparison between SARIMA and FTS Chen in rainfall forecasting, as most prior studies have applied only one of these methods. Therefore, this study was conducted to compare the performance of both methods in order to select the best model and forecast the rainfall in Makassar for 2024.

2. RESEARCH METHODS

2.1 Research Process

The following diagram outlines the steps taken in this research:

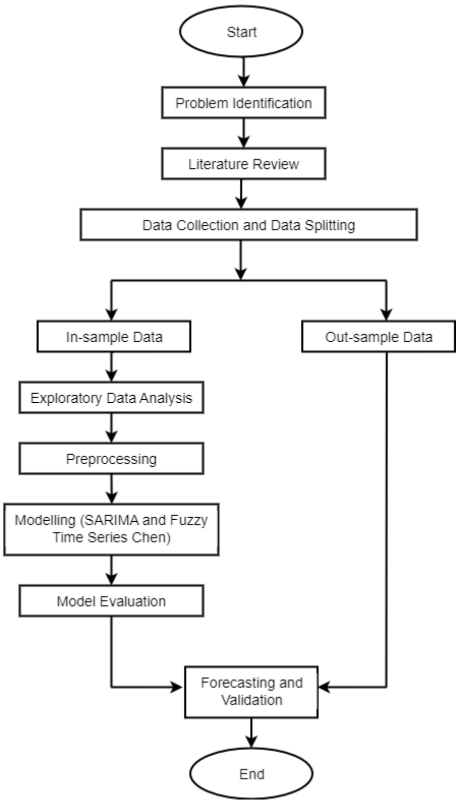


Figure 1. Research Process Diagram

Based on Fig. 1, this study begins with problem identification and a literature review to determine the appropriate forecasting methods, namely SARIMA and Fuzzy Time Series Chen. Rainfall data from the Central Statistics Agency (BPS) Makassar are used and divided into in-sample data (January 2014 – December 2023) for modeling and out-sample data (January 2024 – December 2024) for validation. Following exploratory analysis and preprocessing, both models are constructed and evaluated using MAE and RMSE. The model with the best performance is then applied in the forecasting and validation stage to compare predicted rainfall with actual data.

All analyses in this study were performed using R [20]. The SARIMA modeling was implemented with the forecast package [21], while the Fuzzy Time Series Chen method was carried out using the AnalyzeTS package [22]. Stationarity analysis was conducted using the tseries package [23] for the Augmented Dickey-Fuller and Phillips-Perron tests, and the astsa [24] package for ACF and PACF plots. Model diagnostics, including the Ljung-Box test and Kolmogorov-Smirnov tests, were performed with the stats package [20]. Data visualization was supported by the ggplot2 package [25].

2.2 Seasonal Autoregressive Integrated Moving Average (SARIMA)

The SARIMA $(p, d, q)(P, D, Q)^s$ model is generally represented by the following equation:

$$\phi_{\mathrm{p}}(B)\Phi_{\mathrm{P}}(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t, \tag{1}$$

where:

(p, d, q) : Non-seasonal components;
(P, D, Q) : Seasonal components;
$\phi_p(B)$: Backward shift operator for non-seasonal AR;
$\Phi_P(B^s)$: Backward shift operator for seasonal AR;
$(1-B)^d$: Non-seasonal differencing process of order d;

$(1-B^s)^D$: Seasonal differencing process of order D;
Y_t : Time series at time t;
$\theta_q(B)$: Backward shift operator for non-seasonal MA;
$\Theta_Q(B^s)$: Backward shift operator for seasonal MA;
s : Number of periods in one seasonal cycle;
ε_t : Forecasting error at time t.

2.3 Fuzzy Time Series (FTS) Chen

The steps involved in the FTS Chen are as follows [26]:

1. Determine the Universe of Discourse U

$$U = [D_{min} - D_1; D_{max} + D_2]. \tag{2}$$

2. Determine the Interval Length

   a. Determine the Number of Class Intervals

$$K = 1 + 3.322\log(n). \tag{3}$$

   b. Determine the Range

$$R = (D_{max} + D_2) - (D_{min} + D_1). \tag{4}$$

   c. Determine the Interval Length

$$I = \frac{R}{K}. \tag{5}$$

From the results, the partition of the universe of discourse is obtained according to the interval length.

$$\begin{gathered} u_1 = (D_{min} - D_1\ ;\ D_{min} + D_1 + I), \\ u_2 = (D_{min} - D_1 + I\ ;\ D_{min} - D_1 + 2I), \\ u_3 = (D_{min} - D_1 + 2I\ ;\ D_{min} - D_1 + 3I), \\ \vdots \\ u_n = (D_{min} - D_1 + (K-1)I\ ;\ D_{min} - D_1 + KI). \end{gathered} \tag{6}$$

   d. Finding the Midpoint Value

$$m_i = \frac{lower\ bound + upper\ bound}{2} \tag{7}$$

where:

K : Number of class intervals;
n : Number of observation data;
R : Range;
D_{min} : The smallest data value;
D_{max} : The largest data value;
D_1 : The first constant number set by the researcher;
D_2 : The second constant number set by the researcher;
I : Interval length;
u_n : Partition of the universe of discourse;
m_i : Median of the i interval;

3. Fuzzy Set Classification

Let fuzzy sets $A_1, A_2, \ldots, A_k$, defined by linguistic variables over $U = \{u_1, u_2, \ldots, u_n\}$, represent the k class intervals identified earlier. These fuzzy sets are constructed as follows:

$$A_k = \begin{cases} \frac{1}{u_1} + \frac{1}{u_2}, & if\ k = 1 \\ \frac{0.5}{u_{k-1}} + \frac{1}{u_k} + \frac{0.5}{u_{k+1}}, & if\ 2 \le k \le n-1 \\ \frac{0.5}{u_{n-1}} + \frac{1}{u_n}, & if\ k = n. \end{cases} \tag{8}$$

Here, $\frac{x}{u_k} = x$, represents the membership degree of u_k in the fuzzy set A_k.

4. Fuzzification of Historical Data

   The purpose of fuzzification is to convert numerical (crisp) values into linguistic (fuzzy) values using predefined fuzzy sets. If a data value falls within the interval u_k, it is classified into the corresponding fuzzy set A_k.

5. Fuzzy Logical Relationship (FLR)

   FLR involves establishing connections according to historical data. By observing the connections between fuzzy sets A_i from one period to the next, these connections are organized into an FLR table.

6. Fuzzy Logical Relationship Group (FLRG)

   According to the previous step, FLRs are grouped into categories based on similar current states, ensuring no repetition.

7. Defuzzification

   Defuzzification is the process of converting fuzzy sets into numerical data. In the FTS Chen method, there are several important aspects to consider:

   a. Rule 1: If the current state is A_i and the FLRG of A_i is empty, then the forecast result is the midpoint of u_i. For example, if $A_i \rightarrow \emptyset$, then the forecast = m_i (midpoint u_i).

   b. Rule 2: If the current state is A_i and the FLRG of A_i has a one-to-one relationship, then the forecast result is the midpoint of u_j. For example, if $A_i \rightarrow A_j$, then the forecast = m_j (midpoint u_j).

   c. Rule 3: If the current state is A_i and the FLRG of A_i has a one-to-many relationship, then the forecast result is the average of the midpoints of $u_i, u_j, \dots, u_n$. The forecast can be computed with the equation below:

$$F_t = \frac{m_{i(t-1)} + m_{j(t-1)} + \cdots + m_{n(t-1)}}{n}. \tag{9}$$

2.3 Measurement of Forecast Accuracy

Model performance evaluation provides an overview of how accurately the forecasting model predicts compared to the actual values. The smaller the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, the more accurate the model is in predicting the given data [27].

$$MAE = \left(\frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|\right), \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}}, \tag{11}$$

where:

Y_t : Actual value;
$\hat{Y}_t$: Forecasted value;
n : Total number of data points.

3. RESULTS AND DISCUSSION

3.1 Exploratory Data Analysis

Table 1. Descriptive Statistics

Measure of Central Tendency		Measure of Skewness		Measure of Normality	
Type of Measure	**Value**	**Type of Measure**	**Value**	**Test Statistic**	***p*-value**
Minimum	0	Skewness	1.17077	Kolmogorov-Smirnov	0.00185
Median	152.5				
Mean	275.9				
Maximum	1,195				
Standard Deviation	293.2				

Table 1 shows that the average monthly rainfall in Makassar from January 2014 to December 2023 is classified as moderate rainfall. The minimum and maximum values recorded were 0 mm and 1,195 mm, respectively. The relatively high standard deviation indicates fluctuations in monthly rainfall. Additionally, a p-value of the Kolmogorov-Smirnov test below 0.05 and a skewness of 1.17077 indicate that the data are not normally distributed and tend to be right-skewed, meaning that some months have rainfall significantly above the average.

3.2 Preprocessing

The dataset used in this study contains missing values. Therefore, median imputation was applied, as it is effective for handling skewed or non-normally distributed data [28]. The normality test results in Table 1 confirm that the data are not normally distributed, making a transformation necessary. A square root transformation was chosen because it is suitable for data containing zeros, helps reduce skewness, and tends to normalize the data distribution [29]. The outcomes of this transformation are shown in Table 2.

Table 2. Results of the Square Root Transformation

Year	Month	Actual Data	Transformed Data
2014	January	836.00	28.913
	February	313.00	17.691
	March	311.00	17.635
⋮	⋮	⋮	⋮
2023	Oktober	7.50	2.738
	November	92.40	9.612
	December	190.70	13.809

3.3 Seasonal Autoregressive Integrated Moving Average (SARIMA)

3.3.1 Time Series Plot Identification

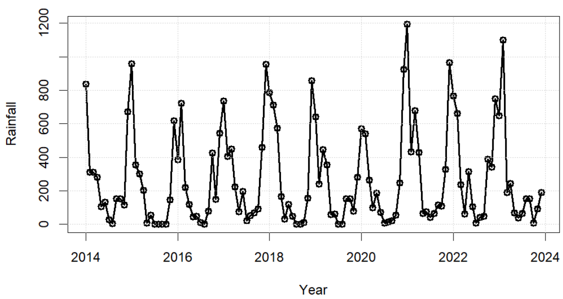
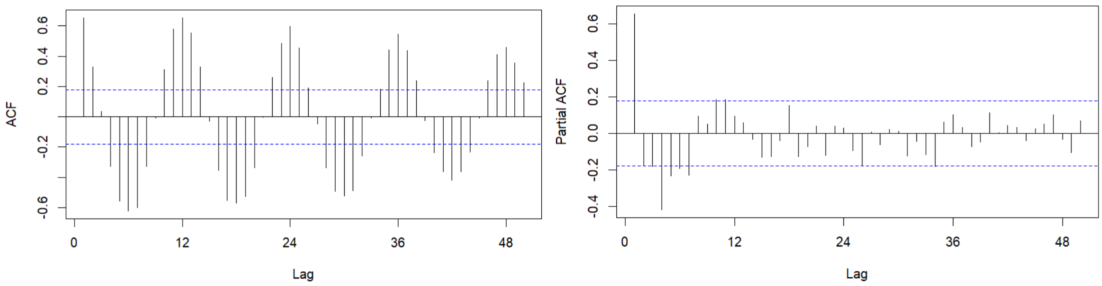


Figure 2. Rainfall Data Plot in Makassar

Fig. 2 indicates that the monthly rainfall in Makassar from January 2014 to December 2023 exhibited significant fluctuations. Rainfall levels tend to increase at the beginning and end of each year, while the remaining months generally experience lower amounts. This recurring pattern suggests the presence of a seasonal trend in the data.

3.3.2 Stationarity Analysis of the Data

In this study, stationarity analysis was carried out using two approaches: first, through the identification of ACF and PACF plots; and second, by employing statistical methods, specifically the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests.



(a) **(b)**

Figure 3. Transformed Data Plots (a) ACF Plot, (b) PACF Plot

Fig. 3 presents a strong seasonal pattern in the ACF plot, indicated by significant spikes at lags that are multiples of 12, reflecting an annual seasonal pattern (12 months). This suggests that there is a significant fluctuation in the mean of the data. In contrast, the PACF plot shows that most lags fall within the significance bounds, indicating that there is no significant fluctuation in the variance of the data.

Table 3. ADF and Phillips-Perron Test Statistics of the Data After Transformation

Test Statistics	p-value	Decision
Augmented Dickey-Fuller	0.4856	H_0 is not rejected
Phillps-Perron	0.01	H_0 is rejected

Table 3 shows that the p-value of the Phillips-Perron test is less than 0.05. Therefore, the null hypothesis (H_0) is rejected, indicating that the data is stationary in terms of variance. On the other hand, the p-value of the ADF test is greater than 0.05. Thus, the null hypothesis (H_0) is not rejected, indicating that the data is non-stationary in terms of mean. Consequently, differencing is required to achieve stationarity in the SARIMA method.

Table 4. ADF and Phillips-Perron Test Statistics After Seasonal Differencing ($D = 1$)

Test Statistics	p-value	Decision
Augmented Dickey-Fuller	0.01	H_0 is rejected
Phillps-Perron	0.01	H_0 is rejected

Table 4 shows that after applying one seasonal differencing step ($D = 1$), both the ADF and Phillips-Perron tests have p-values less than 0.05, indicating that the seasonal component of the data is now stationary. This seasonal differencing was necessary due to the strong annual pattern observed in the ACF plot. However, inspection of non-seasonal lags in the ACF and PACF plots suggested that non-seasonal trends might still be present.

Table 5. ADF and Phillips-Perron Test Statistics After Non-Seasonal Differencing ($d = 1$ and $d = 2$)

Non-Seasonal Differencing ($d = 1$)		
Test Statistics	**p-value**	**Decision**
Augmented Dickey-Fuller	0.13	H_0 is not rejected
Phillps-Perron	0.01	H_0 is rejected
Non-Seasonal Differencing ($d = 2$)		
Test Statistics	**p-value**	**Decision**
Augmented Dickey-Fuller	0.01	H_0 is rejected
Phillps-Perron	0.01	H_0 is rejected

Table 5 shows that after applying the first non-seasonal differencing ($d = 1$), the Phillips-Perron test indicates stationarity in variance (p-value = 0.01), but the ADF test does not reject H_0 (p-value = 0.13), suggesting that the data is not yet fully stationary in mean. By applying a second non-seasonal differencing step ($d = 2$), both tests have p-values less than 0.05, confirming that the data is now fully stationary in both variance and mean.

Based on the results above, the selected differencing orders are $D = 1$ for seasonal differencing and $d = 2$ for non-seasonal differencing. Seasonal differencing ($D = 1$) is applied to remove the annual seasonal effect, while two steps of non-seasonal differencing ($d = 2$) ensure that the data is fully stationary in both mean and variance. This combination satisfies the stationarity assumption required for SARIMA modeling.

3.3.3 SARIMA Model Identification

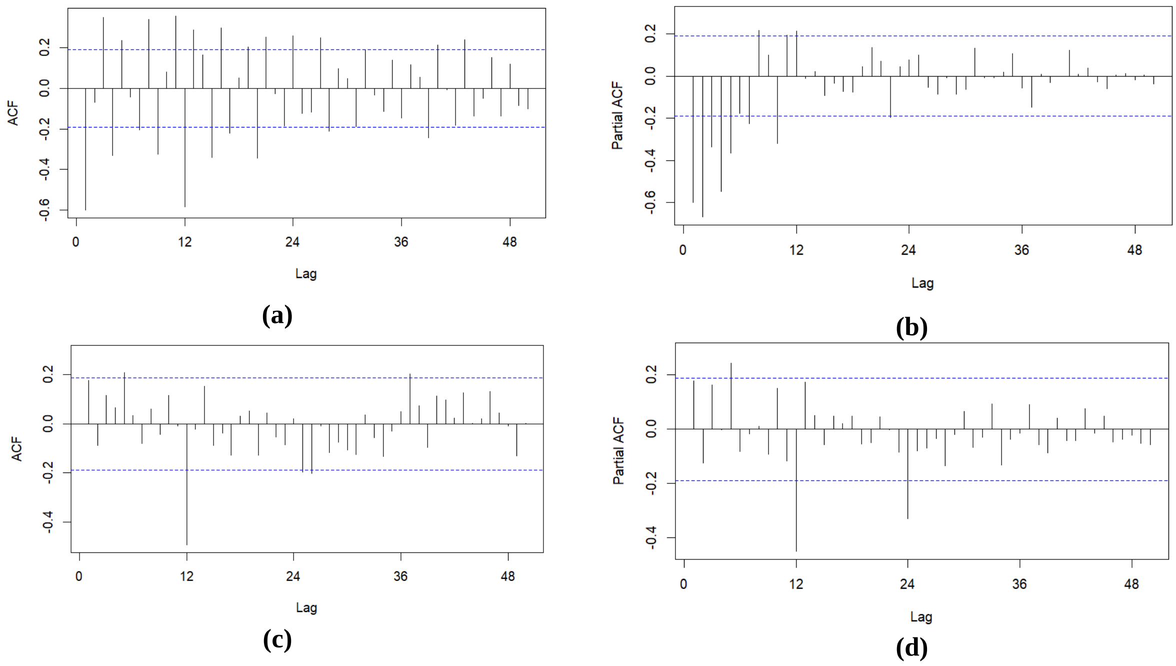


Figure 4. Stationary Non-Seasonal and Seasonal Components Plots
(a) Non-Seasonal ACF Plot, (b) Non-Seasonal PACF Plot, (c) Seasonal ACF Plot, (d) Seasonal PACF Plot

Fig. 4 displays several significant lags in the non-seasonal ACF (lags 1, 3, 4, 5, and 7) and PACF (lags 1, 2, 3, 4, 5, 7, and 10) plots. Accordingly, the non-seasonal moving average orders considered are θ_1, θ_3, θ_4, θ_5, and θ_7, while the non-seasonal autoregressive orders considered are $\emptyset_1$, $\emptyset_2$, $\emptyset_3$, $\emptyset_4$, $\emptyset_5$, $\emptyset_7$, $\emptyset_8$, and $\emptyset_{10}$. Additionally, Fig. 4 presents seasonal ACF and PACF plots, showing a significant lag at 12, corresponding to the first seasonal lag. Therefore, the seasonal moving average and autoregressive orders considered are Θ_1 and Φ_1, respectively. Based on these, a total of 30 tentative models were generated, as presented in Table 6.

Table 6. SARIMA Model Identification

No.	Model
1.	SARIMA(1,2,1)(1,1,1)^{12}
⋮	⋮
7.	SARIMA(2,2,1)(1,1,1)^{12}
⋮	⋮
29.	SARIMA(7,2,3)(1,1,1)^{12}
30.	SARIMA(10,2,3)(1,1,1)^{12}

3.3.4 Parameter Estimation and Significance Testing

The parameter estimation process is carried out using the Maximum Likelihood Estimation method, followed by testing the significance of the estimated parameters.

Table 7. Parameter Estimation Values and Significance Tests

No.	Model	Parameters	Estimation	p-value	Decision
1.	SARIMA(1,2,1)(1,1,1)^{12}	$\emptyset_1$, θ_1, Φ_1, Θ_1	-0.376, -0.999, -0.370, -0.750	0.000, 0.000, 0.001, 0.000	H_0 is rejected
⋮	⋮	⋮	⋮	⋮	⋮

No.	Model	Parameters	Estimation	p-value	Decision
7.	SARIMA$(2,2,1)(1,1,1)^{12}$	$\emptyset_1, \emptyset_2, \theta_1, \Phi_1, \Theta_1$	-0.541, -0.418, -0.998, -0.318, -0.857	0.000, 0.000, 0.000, 0.006, 0.000	H_0 is rejected
⋮	⋮	⋮	⋮	⋮	⋮
29.	SARIMA$(7,2,3)(1,1,1)^{12}$	$\emptyset_1, \emptyset_2, \emptyset_3, \emptyset_4, \emptyset_5, \emptyset_6, \emptyset_7, \theta_1, \theta_2, \theta_3, \Phi_1, \Theta_1$	0.231, -0.835, -0.344, -0.503, -0.303, -0.215, -0.278, -1.989, 1.984, -0.957, -0.276, -0.852	0.042, 0.000, 0.014, 0.000, 0.029, 0.038, 0.016, 0.000, 0.000, 0.000, 0.029, 0.000	H_0 is rejected
30.	SARIMA$(10,2,3)(1,1,1)^{12}$	$\emptyset_1, \emptyset_2, \emptyset_3, \emptyset_4, \emptyset_5, \emptyset_6, \emptyset_7, \emptyset_8, \emptyset_9, \emptyset_{10}, \theta_1, \theta_2, \theta_3, \Phi_1, \Theta_1$	-1.149, -2.008, -1.584, -1.424, -1.174, -1.006, -1.058, -0.833, -0.595, -0.331, -0.511, 0.687, -0.862, -0.405, -0.926	0.000, 0.000, 0.000, 0.000, 0.001, 0.002, 0.000, 0.002. 0.000, 0.004, 0,000, 0.000, 0.000, 0.001, 0.000	H_0 is rejected

Table 7 presents that out of the 30 models analyzed, four models were selected. The parameters of these four models have p-values less than 0.05. Therefore, the null hypothesis (H_0) is rejected for each model, indicating that all parameters are significant in explaining the patterns in the data. Thus, these four models are considered the main candidates for further analysis.

3.3.5 Residual Assumption Tests

1. White Noise Test

This test aims to determine whether the residuals are random. If they are, it means the model has successfully captured all patterns in the data. The test is conducted using the Ljung-Box test.

Table 8. Ljung-Box Test Statistics

Model	p-value	Decision
SARIMA$(1,2,1)(1,1,1)^{12}$	0.0805	H_0 is not rejected
SARIMA$(2,2,1)(1,1,1)^{12}$	0.3817	H_0 is not rejected
SARIMA$(7,2,3)(1,1,1)^{12}$	0.9944	H_0 is not rejected
SARIMA$(10,2,3)(1,1,1)^{12}$	0.9376	H_0 is not rejected

According to Table 8, all four models have p-values greater than 0.05. Therefore, the null hypothesis (H_0) is not rejected for each model, indicating that the residuals of all four models are random. As a result, all four models satisfy the assumption of white noise.

2. Residual Normality Test

This test aims to determine whether the residuals from the model follow a normal distribution. The assessment is conducted using the Kolmogorov-Smirnov test.

Table 9. Kolmogorov-Smirnov Test Statistics

Model	p-value	Decision
SARIMA $(1,2,1)$ $(1,1,1)^{12}$	0.1133	H_0 is not rejected
SARIMA $(2,2,1)$ $(1,1,1)^{12}$	0.0662	H_0 is not rejected
SARIMA $(7,2,3)$ $(1,1,1)^{12}$	0.0782	H_0 is not rejected
SARIMA $(10,2,3)$ $(1,1,1)^{12}$	0.3355	H_0 is not rejected

According to Table 9, all four models have p-values greater than 0.05. Therefore, the null hypothesis (H_0) is not rejected, indicating that the residuals of all four models follow a normal distribution. As a result, all models satisfy the assumption of normality.

3.3.6 AIC Value Selection

The next step is to compare the AIC values of the four models. A smaller AIC value indicates that the model achieves a better balance between complexity and explanatory power in capturing the data patterns.

Table 10. AIC Comparison

Model	AIC
SARIMA$(1,2,1)(1,1,1)^{12}$	693.53
SARIMA$(2,2,1)(1,1,1)^{12}$	676.54

Model	AIC
SARIMA(7,2,3)(1,1,1)^{12}	**672.62**
SARIMA(10,2,3)(1,1,1)^{12}	675.19

According to Table 10, the model with the smallest AIC value is SARIMA(7,2,3)(1,1,1)^{12}. Therefore, this model is considered the most suitable for forecasting.

3.4 Fuzzy Time Series (FTS) Chen

3.4.1 Determine the Universe of Discourse *U*

The data have a minimum value of 0 and a maximum value of 34,568. Assuming $D_1 = D_2 = 0$, the universe of discourse is determined using Eq. (2), yielding the following result:

$$U = [0 - 0\ ;\ 34.568 + 0] = [0\ ;\ 34.568].$$

In this study, the values of D_1 and D_2 were set to 0 because the data after transformation did not exhibit extreme outliers, so no extension or contraction of the universe of discourse was required. This approach is also consistent with previous studies [30] that applied $D_1 = D_2 = 0$ when the data were within a stable range. To strengthen this decision, additional trials with D_1 and $D_2 \neq 0$ were conducted. However, the results did not improve the forecasting accuracy, so the values $D_1 = D_2 = 0$ were ultimately selected.

3.4.2 Determine the Interval Length

1. Determine the Number of Class Intervals

The number of class intervals is calculated using Eq. (3), with $n = 120$, resulting in the following outcome:

$$K = 1 + 3.322 \times \log(120) = 1 + 3.322 \times 2.079\ ; K = 7.906 \approx 8.$$

In this study, the number of fuzzy intervals was determined using Sturges' rule, taking the sample size into account, resulting in $K = 8$. This choice is appropriate because it balances the representation of data variation and interval frequency. Validation with several alternative values of K showed that this setting provided the best forecasting accuracy, with MAE and RMSE values not significantly different from the nearest alternatives, thereby reinforcing the empirical basis for this selection.

2. Determine the Range

The range is calculated using Eq. (4), resulting in:

$$R = (34.568 + 0) - (0 + 0) = 34.568.$$

3. Determine the Interval Length

The interval length is calculated using Eq. (5), resulting in:

$$I = \frac{34.568}{8} = 4.321.$$

4. Finding the Midpoint ($\boldsymbol{m_i}$)

The universe of discourse is partitioned by interval length using Eq. (6), resulting in:

$$u_1 = [0\ ; 4.321]$$
$$u_2 = (4.321\ ; 8.642]$$
$$u_3 = (8.642\ ; 12.963]$$
$$\vdots$$
$$u_8 = (30.247\ ; 34.568]$$

After determining the intervals $\boldsymbol{u_1}$ to $\boldsymbol{u_8}$, the midpoint of each class interval is calculated using Eq. (7), based on the lower and upper bounds, as presented in Table 11.

Table 11. Midpoint (m_i)

Class	Lower Bound	Upper Bound	Midpoint (m_i)
u_1	0	4.321	2.161
u_2	4.321	8.642	6.482
u_3	8.642	12.963	10.803
u_4	12.963	17.284	15.124
u_5	17.284	21.605	19.445
u_6	21.605	25.926	23.766
u_7	25.926	30.247	28.087
u_8	30.247	34.568	32.408

3.4.3 Fuzzy Set Classification

The fuzzy sets $A_1, A_2, \dots A_8$ are determined based on the intervals $(u_1, u_2, \dots u_8)$ formed in the previous step, by adapting the model in Eq. (8).

$$A_1 = \frac{1}{u_1} + \frac{0,5}{u_2} \qquad A_3 = \frac{0,5}{u_2} + \frac{1}{u_3} + \frac{0,5}{u_4} \qquad A_5 = \frac{0,5}{u_4} + \frac{1}{u_5} + \frac{0,5}{u_6} \qquad A_7 = \frac{0,5}{u_6} + \frac{1}{u_7} + \frac{0,5}{u_8}$$

$$A_2 = \frac{0,5}{u_1} + \frac{1}{u_2} + \frac{0,5}{u_3} \qquad A_4 = \frac{0,5}{u_3} + \frac{1}{u_4} + \frac{0,5}{u_5} \qquad A_6 = \frac{0,5}{u_5} + \frac{1}{u_6} + \frac{0,5}{u_7} \qquad A_8 = \frac{0,5}{u_7} + \frac{1}{u_8}$$

Here, each fuzzy set A_i corresponds to an interval class u_i. For example, A_1 represents the interval u_1 = [0, 4.321], A_2 represents u_2 = (4.321, 8.642], and so on until A_8 which represents u_8 = (30.247, 34.568]. These fuzzy sets provide the linguistic labels used in the fuzzification process. In other words, A_1 can be interpreted as the fuzzy set for "very low rainfall", A_2 as "low rainfall", A_3 as "moderately low rainfall", and so forth, up to A_8 as "very high rainfall".

3.4.4 Fuzzification of Historical Data

This step converts numerical values into linguistic (fuzzy) values using the defined fuzzy sets.

Table 12. Fuzzification

Year	Month	Data	Fuzzification
2014	January	28.913	A_7
	February	17.691	A_5
	March	17.635	A_5
⋮	⋮	⋮	⋮
2023	October	2.738	A_1
	November	9.612	A_3
	December	13.809	A_4

According to Table 12, the data for January 2014, which is 28.913, falls into the fuzzy set A_7 because the value lies within the interval class u_7. The data for February 2014, which is 17.691, falls into the fuzzy set A_5 because the value lies within the interval class u_5. A similar process is applied to the data for the subsequent months up to December 2023, where the value 13.809 falls into the fuzzy set A_4, as it lies within the interval class u_4.

3.4.5 Fuzzy Logical Relationship (FLR)

This relationship is formed based on the sequence of values from time $\boldsymbol{t}$ to time $\boldsymbol{t+1}$ within a fuzzy structure.

Table 13. Fuzzy Logical Relationship (FLR)

Year	Month	FLR
2014	January	NA $\rightarrow A_7$
	February	$A_7 \rightarrow A_5$
	March	$A_5 \rightarrow A_5$
⋮	⋮	⋮
2023	October	$A_3 \rightarrow A_1$
	November	$A_1 \rightarrow A_3$
	December	$A_3 \rightarrow A_4$

According to Table 13, the FLR shows the relationship between the fuzzification of one month and the following month. For instance, in January 2014, since there is no earlier data, it is recorded as NA $\rightarrow A_7$. In February 2014, the fuzzification in January is A_7 and the fuzzification in February is A_5, forming the relationship $A_7 \rightarrow A_5$. In March 2014, the fuzzification in February is A_5 and the fuzzification in March is also A_5, resulting in the relationship $A_5 \rightarrow A_5$. This process continues sequentially until November 2023, which relates to December 2023.

3.4.6 Fuzzy Logical Relationship Group (FLRG)

The next step is to group the results from the previous step into several categories according to similar current states, ensuring no repetition.

Table 14. Fuzzy Logical Relationship (FLRG)

Current State		Next State
A_1	$\rightarrow$	A_1, A_2, A_3
A_2	$\rightarrow$	A_1, A_2, A_3, A_4, A_5
A_3	$\rightarrow$	$A_1, A_2, A_3, A_4, A_5, A_6, A_7$
A_4	$\rightarrow$	$A_1, A_2, A_3, A_4, A_5, A_6, A_8$
A_5	$\rightarrow$	$A_2, A_3, A_4, A_5, A_7, A_8$
A_6	$\rightarrow$	$A_3, A_4, A_5, A_6, A_7, A_8$
A_7	$\rightarrow$	A_4, A_5, A_6, A_7, A_8
A_8	$\rightarrow$	A_4, A_5, A_7, A_8

Table 14 presents the relationships between states. For example, if the current state is A_1, then the next state is likely to be A_1,A_2, or A_3. If the current state is A_2, then the next state is likely to be A_1,A_2,A_3,A_4, or A_5. This pattern continues similarly up to the current state A_8.

3.4.7 Defuzzification

After forming the FLRG, defuzzification is carried out to convert a fuzzy set into numerical values using Eq. (9).

Table 15. Defuzzification

FLRG	F(t)	FLRG Defuzzification
$A_1 \rightarrow A_1, A_2, A_3$	$\frac{m_1+m_2+m_3}{3}$	6.481
$A_2 \rightarrow A_1, A_2, A_3, A_4, A_5$	$\frac{m_1+m_2+m_3+m_4+m_5}{5}$	10.802
$A_3 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6, A_7$	$\frac{m_1+m_2+m_3+m_4+m_5+m_6+m_7}{7}$	15.123
$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6, A_8$	$\frac{m_1+m_2+m_3+m_4+m_5+m_6+m_8}{7}$	15.741
$A_5 \rightarrow A_2, A_3, A_4, A_5, A_7, A_8$	$\frac{m_2+m_3+m_4+m_5+m_7+m_8}{6}$	19.444
$A_6 \rightarrow A_3, A_4, A_5, A_6, A_7, A_8$	$\frac{m_3+m_4+m_5+m_6+m_7+m_8}{6}$	21.605
$A_7 \rightarrow A_4, A_5, A_6, A_7, A_8$	$\frac{m_4+m_5+m_6+m_7+m_8}{5}$	23.766
$A_8 \rightarrow A_4, A_5, A_7, A_8$	$\frac{m_4+m_5+m_7+m_8}{4}$	23.766

After obtaining the FLRG defuzzification values presented in Table 15, they can be directly applied to the entire dataset. These values serve as the model outputs for all data, as presented in Table 16.

Table 16. Forecasting Results

Year	Month	Defuzzification
2014	January	NA
	February	23.766
	March	19.444
⋮	⋮	⋮
2023	October	15.123
	November	6.481
	December	15.123

According to Table 16, there is no forecast result for January 2014 because the FTS Chen model can only predict for the subsequent period $(t+1)$. For February 2014, the forecasted value is 23.766 because January 2014 falls within the fuzzy set A_7, which has a defuzzified value of 23.766. This process continues until December 2023, where the forecasted value is determined based on the fuzzy set of the previous month, November 2023.

3.5 Model Evaluation

The evaluation of the SARIMA $(7,2,3)(1,1,1)^{12}$ model and the FTS Chen model was conducted based on the calculation of MAE using Eq. (10) and RMSE using Eq. (11).

Table 17. Model Evaluation of SARIMA $(7,2,3)(1,1,1)^{12}$ and FTS Chen

Model	MAE	RMSE
SARIMA$(7,2,3)(1,1,1)^{12}$	2.654	3.846
Fuzzy Time Series Chen	5.575	6.594

Table 17 presents that the SARIMA $(7,2,3)(1,1,1)^{12}$ model achieved lower MAE and RMSE values, specifically 2.654 and 3.846, compared to 5.575 and 6.594 for the FTS Chen model. While the FTS Chen method provides flexibility in handling uncertainty, its forecasts tend to deviate more during extreme rainfall months and fail to fully capture seasonal fluctuations. In contrast, SARIMA explicitly models seasonal and autoregressive components, allowing it to closely track both the peaks and troughs of rainfall patterns. To further illustrate these findings, Fig. 5 presents a visual comparison between actual data, SARIMA$(7,2,3)(1,1,1)^{12}$ forecasts, and FTS Chen forecasts.

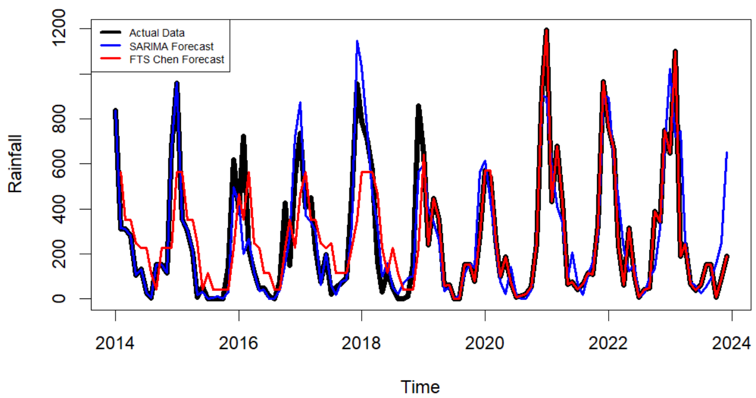


Figure 5. Plot of Comparison Between Actual Data, SARIMA Forecast, and FTS Forecast

Based on Fig. 5, it can be seen that SARIMA (blue line) is able to consistently follow the actual data (black line), both during rainy season peaks and dry season troughs. This indicates that SARIMA successfully captures the seasonal component and short-term dependencies, resulting in more accurate forecasts. On the other hand, the FTS Chen model (red line) shows greater deviations, especially during extreme rainfall periods, where the predictions appear smoother and less responsive to sharp fluctuations. This visual evidence reinforces the numerical evaluation in Table 17, confirming that SARIMA $(7,2,3)(1,1,1)^{12}$ is the more suitable model for forecasting rainfall in this study. Based on Eq. (1), this model can be expressed as follows:

$$(1-0.231B+0.835B^2+0.344B^3+0.503B^4+0.303B^5+0.215B^6+0.278B^7)(1+0.276B^{12})$$
$$(1-B)^2\,(1-B^{12})Y_t=(1+1.989B-0.984B^2+\,0.957B^3)(1+\,0.852B^{12})\varepsilon_t.$$

3.6 Forecasting and Validation

Forecasting rainfall in Makassar for the year 2024 was carried out using the SARIMA $(7,2,3)(1,1,1)^{12}$ model, as shown below.

Table 18. Comparison Between Actual Data and Forecasted Results

Period	Actual Data (mm)	SARIMA Forecast (mm)
January 2024	556.0	439.5
February 2024	465.6	196.1
March 2024	262.2	151.2
April 2024	107.0	105.5

Period	Actual Data (mm)	SARIMA Forecast (mm)
May 2024	15.8	91.9
June 2024	47.6	33.1
July 2024	78.4	23.6
August 2024	0.2	78.8
September 2024	12.6	19.2
October 2024	46.8	23.7
November 2024	330.8	108.4
December 2024	1,105.4	507.5

Table 18 shows the differences between the forecasted and actual rainfall values for several months. For instance, in February 2024, the actual rainfall reached 465.6 mm, whereas the forecast was only 196.1 mm. Conversely, the forecasts were relatively accurate from April to July, as well as in September and October 2024. For example, in April, the actual rainfall was 107.0 mm, whereas the forecast was 105.5 mm.

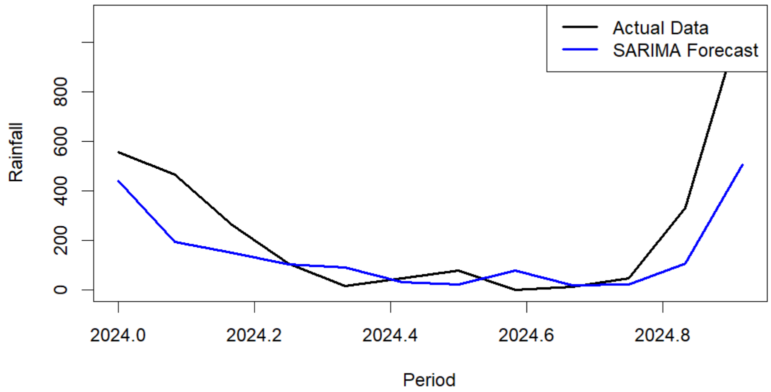


Figure 6. Plot of Comparison Between Actual Data and SARIMA Forecast

Furthermore, Fig. 6 illustrates that the SARIMA $(7,2,3)(1,1,1)^{12}$ model effectively captured the seasonal rainfall patterns, showing a similar trend between the actual and forecasted results. The rainy season was observed at the beginning and end of the year, while the dry season occurred mid-year. Overall, the SARIMA $(7,2,3)(1,1,1)^{12}$ model demonstrated satisfactory performance in forecasting rainfall in Makassar for 2024.

4. CONCLUSION

The research results indicated that the SARIMA $(7,2,3)(1,1,1)^{12}$ was the best model compared to the FTS Chen model in forecasting rainfall in Makassar. The SARIMA $(7,2,3)(1,1,1)^{12}$ model achieved lower MAE and RMSE values, namely 2.654 and 3.846, respectively, whereas the FTS Chen model had an MAE of 5.575 and an RMSE of 6.594. Forecasting rainfall for 2024 in Makassar using this model proved effective in capturing seasonal patterns. Although there were considerable differences in certain months—specifically January, February, March, August, November, and December 2024—the model successfully distinguished between the rainy and dry seasons. More accurate forecasts were observed from April to July, as well as in September and October 2024. Overall, the SARIMA $(7,2,3)(1,1,1)^{12}$ model demonstrated reliable and accurate performance in forecasting rainfall in Makassar for 2024. However, this study has limitations, as it relies solely on historical rainfall data and does not consider other meteorological variables such as temperature, humidity, or wind patterns. Future research could explore hybrid models and include these factors to improve forecasting accuracy.

Author Contributions

Gavrilla Claudia: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing Original Draft Preparation. Atika Ratna Dewi: Software, Resources, Visualization, Validation. Aina Latifa Riyana Putri: Investigation, Project Administration, Funding Acquisition. All authors have read and agreed to the published version of the manuscript, discussed the results together, and contributed to the refinement of the final draft.

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Declarations

The authors declare that there are no conflicts of interest regarding the publication of this study.

Declaration of Generative AI and AI-assisted Technologies

AI-assisted technology (ChatGPT) was used to support light paraphrasing and sentence restructuring for clarity. The authors confirm that the underlying ideas, arguments, data analyses, and conclusions are original and were not generated by AI. All AI-assisted edits were critically reviewed and validated by the authors.

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