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PREDICTION OF AVERAGE TEMPERATURE IN BANYUWANGI REGENCY USING SARIMA

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ABSTRACT

Climate change due to human activity has significantly impacted increasing global average temperatures, including in Banyuwangi Regency, East Java. The impact is felt in several sectors, such as agriculture, tourism, and health. As a preventive measure to minimize the adverse effects that will occur in the future, an accurate prediction of the average temperature of Banyuwangi Regency is needed. This research used secondary data from the official website of the Central Statistics Agency (BPS) of Banyuwangi Regency per month from January 2012 to December 2023. Predictions are made using the seasonal autoregressive integrated moving average (SARIMA) approach. The best model is selected based on its fulfillment of stationarity, the significance of its parameters, and compliance with the assumptions of normality and white noise. From this method, the best model obtained to predict the average temperature of Banyuwangi Regency is the probabilistic SARIMA (1,0,0)(0,1,1)12. The probabilistic SARIMA model treats both parameters and forecasts as probability distributions. The average temperature of Banyuwangi Regency is obtained for the next year, namely from January 2023 to December 2023, with a MAPE of 1.63%. With an accuracy rate of 98.37%, it can be said that the probabilistic SARIMA (1,0,0)(0,1,1)12 model is accurate in predicting the average temperature of Banyuwangi Regency in the future. Thus, the prediction of the average temperature of Banyuwangi Regency is expected to help the community and government manage the impact of erratic climate change to improve the welfare of all Banyuwangi people.

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1. INTRODUCTION

Since the industrial revolution, human activities such as fossil fuel combustion and deforestation have increased greenhouse gas emissions (CO2, CH4, N2O), contributing to climate change. These gases trap atmospheric heat, increase global temperatures, and trigger extreme weather phenomena such as El Nino [1]. The head of BMKG, Dwikoria Karnawati, said 2023 could be the hottest year ever recorded, surpassing 2016 [2]. This El Nino phenomenon occurs due to warming sea surface temperatures in the Pacific Ocean [3].

Banyuwangi Regency, which is located on the eastern tip of Java Island, is affected by climate change, especially in the agricultural sector. Drought due to El Nino reduced rice productivity by 4.992 tons or about 5% in 2023 [4]. In addition, Banyuwangi is famous for its tourism sector, as are Ijen Crater and Red Island Beach. Seeing the magnitude of the impact of climate change, an accurate temperature prediction effort is needed to help the community and government overcome the impacts.

Temperature is one of the primary factors driving global climate change. Significant temperature fluctuations can have far-reaching consequences for human life and the environment, including increased evaporation that accelerates the hydrological cycle, increased rainfall, and long-term climate pattern shifts. Additionally, rising temperatures can lead to heat waves, heightened risks of heat-related illnesses, and ecosystem changes that affect both animal and plant species [5].

One method commonly used to forecast temperature data with seasonal patterns is SARIMA [6]. SARIMA is an extension of the ARIMA model designed to handle time series data with recurring seasonal trends, such as weekly, monthly, or annual cycles. The performance of these models is usually evaluated using MAPE, where a lower MAPE value indicates better forecasting accuracy. While time series models such as SARIMA have been widely adopted for temperature forecasting across various regions, there remains a noticeable scarcity of research targeting localized contexts, particularly in Banyuwangi Regency. Studies conducted at broader spatial scales, such as national or provincial levels, may overlook critical microclimatic dynamics that influence local temperature variations.

Additionally, a significant portion of the existing literature focuses predominantly on performance metrics like RMSE or MAE, often without adequate evaluation of fundamental statistical assumptions required for robust time series modeling, stationarity, parameter significance, normality, and the presence of white noise. This shortfall potentially undermines the reliability and interpretability of the resulting models.

Moreover, despite the increasing relevance of probabilistic approaches in enhancing predictive insights by accounting for model uncertainty, the application of probabilistic SARIMA in temperature forecasting—especially within complex and heterogeneous geographic regions like Banyuwangi—has not been sufficiently explored. Given SARIMA's inherent capacity to effectively model seasonal time series data, it is well-suited for temperature datasets that typically demonstrate cyclical annual behavior. Nevertheless, comprehensive studies that apply SARIMA at a district level while rigorously validating model assumptions and integrating uncertainty are currently limited in the literature.

An additional strength of the SARIMA model lies in its adherence to the statistically rigorous framework of the Box-Jenkins methodology, which enables a structured process of model identification, parameter estimation, and diagnostic evaluation that can be empirically validated. Consequently, SARIMA provides high forecasting accuracy and a more comprehensive understanding of seasonal patterns within time series data, an advantage often lacking in more conventional approaches such as exponential smoothing or basic time series regression models.

Similar research in the Ashanti Region, Ghana, using the SARIMA method to predict monthly temperature showed the best model $(2,1,1)(1,1,2)^{12}$ with a MAPE of 1.408% [7]. In other studies, when SARIMA compared to Holt Winter's exponential smoothing method with the $\alpha = 0.2, \beta = 0.5,\ \gamma = 0.1$ in export data in West Sumatra. Result from that research, the best method is SARIMA $(1,1,1)(0,1,1)^{12}$ model with a smaller MAPE value of 0.437% than the MAPE value of Holt Winter is 0.894% [8]. In Banyuwangi, average temperature prediction research has never been conducted. However, the SARIMA method is considered appropriate because the temperature data has a seasonal pattern. SARIMA, a development of the ARIMA(Box-Jenkins) model, is specifically designed for time series data with seasonal patterns, making it suitable for predicting monthly average temperatures in Banyuwangi [9].

2. RESEARCH METHODS

This research uses quantitative methods that use data in the study, from data collection to interpretation to results and conclusions [10]. The quantitative time series approach, particularly the Box-Jenkins method, is a systematic framework for modeling and forecasting time series data based on historical patterns using statistical models such as SARIMA. The research used secondary data from the official website of the Central Statistics Agency (BPS) of Banyuwangi Regency in the form of the average temperature of Banyuwangi Regency per month from January 2012 to December 2023 [11]. This research utilizes two types of data: training data and testing data. Training data is used to develop the model while testing data evaluates its performance by comparing its forecasts with actual observed values. This study used monthly average temperature data from January 2012 to December 2022 as training data, and the remaining data from January 2023 to December 2023 was used as testing data. The analysis will be conducted using the SARIMA method through the following steps.

The first step is to describe the average temperature data of Banyuwangi Regency per month from January 2012 to December 2023 using graphs and descriptive statistics. The second step is modeling using the SARIMA approach. This step begins with identifying data stationarity using Trend Analysis, ACF, and PACF plots and performing the Augmented Dickey-Fuller Test (ADF). A time series process is considered stationary if it shows no trend change in mean or variance over time [12]. The calculation of the ACF value of sample lag is formulated as follows [13].

$$r_k = corr(Z_t, Z_{t-k}) = \widehat{\rho_k} = \frac{\sum_{t=1}^{n-k}(Z_t - \bar{Z})(Z_{t-k} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2} \tag{1}$$

The ACF value indicates the amount of correlation (linear relationship) between observations at the current time t and observations at previous times $(t-1, t-2, \dots, t-k)$. Meanwhile, according to Wei (1990) in Jekir et.al (2021) the partial autocorrelation value is mathematically formulated as follows [14].

$$\phi_{k+1,k+1} = \frac{\rho_{k+1} - \sum_{j=1}^{k=1} \phi_{kj}\rho_{k+1-j}}{1 - \sum_{j=1}^{k=1} \phi_{kj}\rho_j} \tag{2}$$

The PACF value indicates the level of partial correlation (linear relationship separately) between the current observation at time t and observations from previous time periods $(t-1, t-2, \dots, t-k)$. Data is said to be stationary in the ADF test if the coefficient value shows $|\rho| > 1$, but if the coefficient shows $|\rho| = 1$, then the data is said to be non-stationary [15]. After that, the Box-Cox Transformation is applied to make the data more stationary in terms of variance by considering the Rounded Value (λ) to determine the appropriate data transformation, while differencing is performed both non-seasonal and seasonal to stationary the data in the mean.

After the data is stationary, the formulation of a possible SARIMA model appropriate for further analysis is carried out based on the lag values that come out on the ACF and PACF plots. The SARIMA model is generally represented as ARIMA (p,d,q)(P,D,Q)^S. SARIMA is a development of the ARIMA model and is appropriate for data with a seasonal pattern with the following mathematical form [16].

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D Z_t = \theta_q(B)\Theta_Q(B^S)a_t \tag{3}$$

with,

$\phi_p(B) \quad = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

$\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \phi_P B^{PS}$

$\theta_q(B) \quad = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}$

Furthermore, the parameter significance test, white noise residual assumption test, and normal distribution are carried out on several predetermined models. After testing, the best model is obtained using the concept of parsimony and continued by conducting a homoscedasticity test. After obtaining the best model, then formulate the model equation.

The last step is to predict using the best SARIMA model that has been obtained. This step begins with transforming the forecasting results according to the Rounded Value (λ) value. Next, the results of the forecasting transformation are compared with the test data, namely the average temperature data of Banyuwangi Regency per month from January 2023 to December 2023 and the MAPE value. This value is used to assess the accuracy of the statistical model by calculating the difference between actual data and forecasting results [17] with the following mathematical form.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{Z_t - F_t}{Z_t} \times 100\% \tag{4}$$

With Z_t is the actual data, F_t is the data forecasting results, and n is the number of data [16]. According to Lewis and Colin David (1982) in Arwin et al. (2020) there is an interpretation of the MAPE value of the data seen from the value interval, which is presented in Table 1 below [17].

Table 1. Interpretation of MAPE

Range MAPE	Interpretation
< 10 %	Precise model
10 – 20 %	Adequate model
20 – 50 %	Decent model
> 50 %	Imprecise model

Based on Table 1, it is shown that models with low MAPE also have a low error rate in predicting actual data. When the MAPE value is less than 10%, the accuracy of model prediction is included in the precise model category; otherwise, when the MAPE value is more than 50%, the model is included in the imprecise model. Therefore, the minimum MAPE value is the better the model's ability to predict and the more reliable the model is.

3. RESULTS AND DISCUSSION

3.1 Data Description

Based on data obtained from BPS official webpage of Banyuwangi Regency, an overview of the average temperature of Banyuwangi Regency in the period January 2012 to December 2023 is obtained through the time series graph as follows.

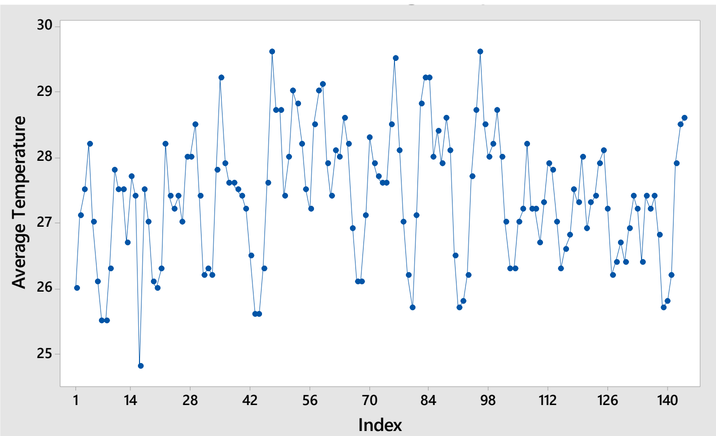


Figure 1. Time Series Graph of Average Temperature of Banyuwangi Regency Period January 2012 - December 2023

Figure 1, shows that the average temperature of Banyuwangi Regency from January 2012 to December 2023 fluctuates monthly. The time series graph illustrates a dynamic and non-linear pattern, indicating considerable seasonal and annual variation in average temperature. Each point on the graph represents the average temperature for a specific month, and the connecting lines visualize the continuity of temperature changes over time. It is evident that the temperature does not follow a consistent upward or downward trend; instead, it exhibits periodic cycles with relatively stable variation. This suggests the influence of seasonal climate patterns and other external environmental factors on the region's temperature behavior.

Over the twelve years, peaks in temperature appear irregularly distributed, indicating that the highest temperatures do not occur at fixed intervals each year. Similarly, the lowest temperature points are scattered across different months, suggesting variability in the timing and intensity of cooling periods. These fluctuations may reflect the impact of monsoon cycles, local topography, and potential effects of global climate change.

The lowest average temperature in Banyuwangi Regency was recorded in April 2013, while the highest average temperatures were observed in November 2015 and December 2019. The temperature in April 2013 reached the lowest point on the graph, which may have been influenced by high rainfall, dense cloud cover, or reduced solar radiation. Conversely, the peaks in November 2015 and December 2019 may correspond to periods of extreme heat, possibly due to prolonged dry seasons, El Niño phenomena, or local factors such as urban heat effects and land-use changes. These observations highlight the importance of further analysis into regional and global climatic drivers that influence the temperature trends in Banyuwangi Regency over time.

Table 2. Descriptive Statistics of Average Temperature Data of Banyuwangi Regency for the Period January 2012 - December 2023

	Total Count	Mean	Standard Deviation	Minimum	Median	Maximum
Average Temperature Banyuwangi	144	27.387	0.983	24.8	27.4	29.6

Table 2 shows that from 144 data, the lowest average temperature of Banyuwangi Regency in the period January 2012 to December 2022 was 24.8°C, while the highest average temperature was 29.6°C with an average of 27.387 °C or 27.4°C.

3.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) Modeling

The first step in time series analysis is determining whether the data is stationary in mean and variance.

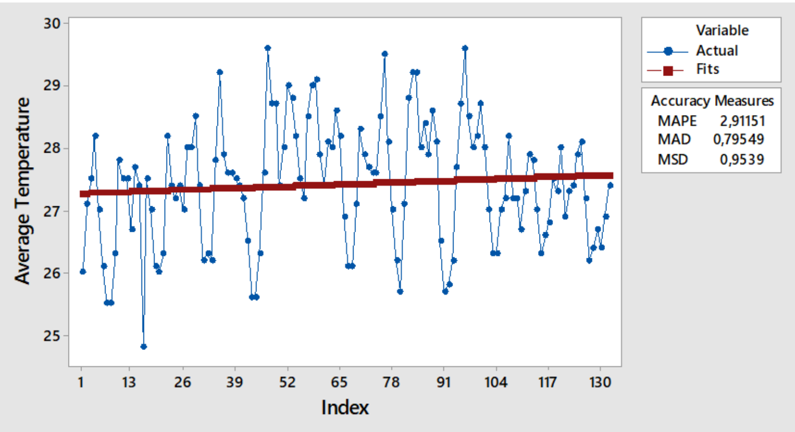
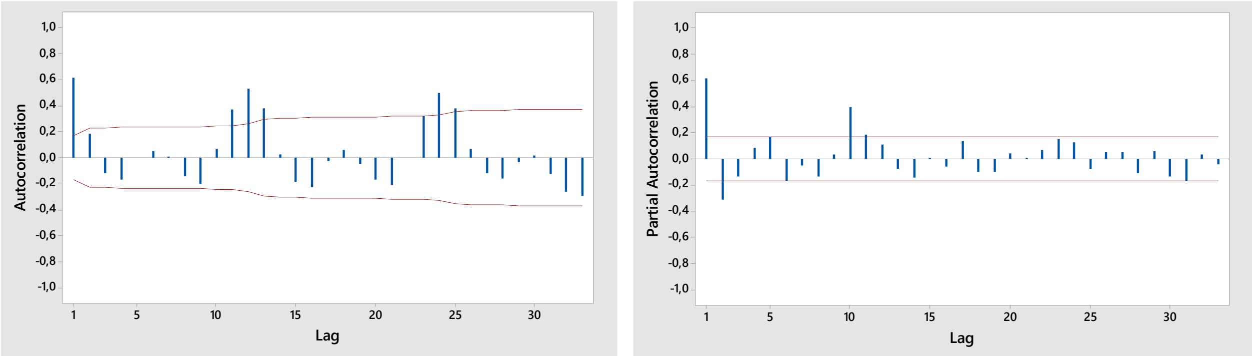


Figure 2. Trend Analysis Plot of Average Temperature of Banyuwangi Regency for the Period January 2012 - December 2022

From **Figure 2**, the data tends to form a constant trend, or there is no tendency for an upward or downward trend, which indicates that the data is stationary in the mean, so non-seasonal differencing is not required.



(a) (b)

Figure 3. (a) ACF Plot and (b) PACF Plot of Average Temperature of Banyuwangi Regency for the Period January 2012 - December 2022

The ACF plot in Figure 3 shows that the data forms a sinusoidal pattern, which is seasonal data. Meanwhile, the PACF plot indicates that several lags come out of the significant limits line, namely at lags 1, 11, 12, 13, 24, and 12. From the two plots above, it can be seen that there are always lags that come out at lag 12 or multiples of it, so it is necessary to do seasonal differencing at lag 12 in the hope that non-seasonal and seasonal lags that come out of the significant limit line on the ACF and PACF plots can be more apparent. In addition to identifying data stationarity in the mean, data stationarity in variance is also identified using Box-Cox Transformation with the following results.

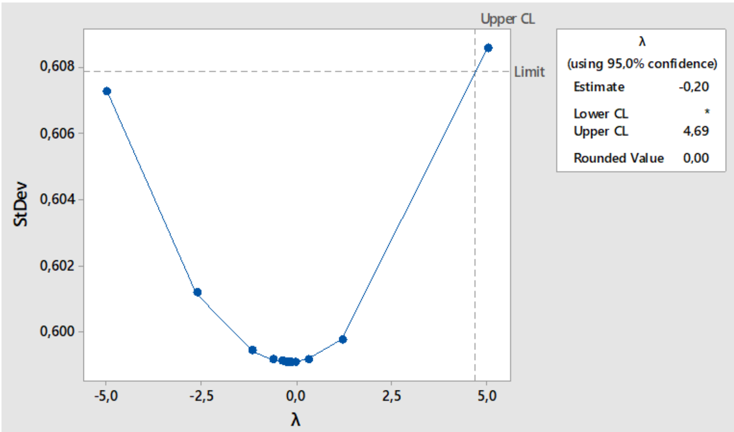


Figure 4. Box-Cox Transformation Plot of Average Temperature of Banyuwangi Regency for the Period January 2012 - December 2022

From Figure 4, the Box-Cox transformation results show a Rounded Value (λ) of 0.00, which indicates that the average temperature data for Banyuwangi Regency is not stationary on variance. Furthermore, it is necessary to transform the data into the form ln (Z_t) to stationary the data in variance. After identifying the stationarity of the data, it was found that the data was stationary in the mean. Still, the data must be seasonally different at lag 12, to facilitate the determination of the model.

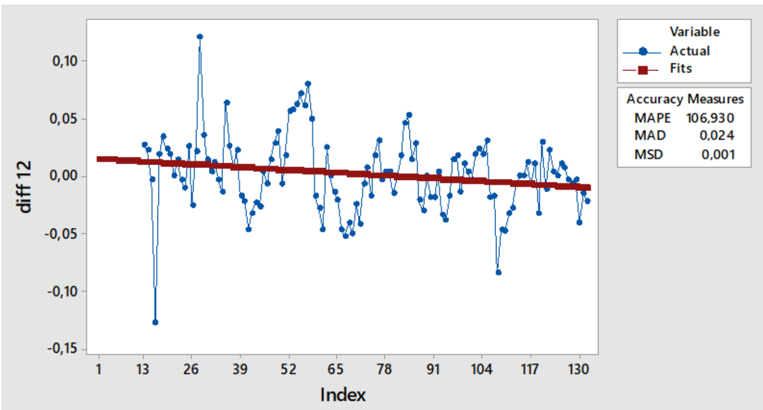


Figure 5. Plot Trend Analysis Differencing Lag 12 Average Temperature of Banyuwangi Regency Period January 2012 - December 2022

Figure 5 shows that after seasonal differencing at lag 12, the data tends to form a constant trend, although there is a slight decrease in trend compared to the previous plot. The ADF Test can be conducted with the hypothesis to ensure the data is stationary.

H_0 : Banyuwangi Regency average temperature data is not stationary.

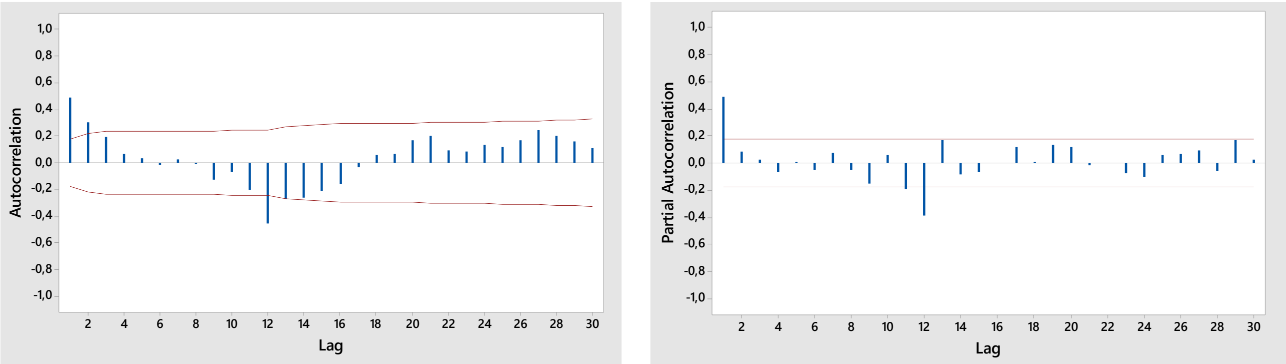
H_1 : Banyuwangi Regency average temperature data is stationary.

With a confidence interval of 95%, the critical region for this test is to reject H_0 if the p-value < alpha (5%).

Table 3. ADF Test Results Differencing Lag 12 Average Temperature of Banyuwangi Regency for the Period January 2012 - December 2022

Augmented Dickey-Fuller Test	
Dickey-Fuller	P-Value
-3.9778	0.01253

Based on **Table 3**, with the ADF Test, the p-value is 0.01253. This value is smaller than the alpha value (5%) so the decision to reject H_0 is taken. Thus, it can be concluded that after seasonal differencing at lag 12, the Banyuwangi average temperature data for January 2012 to December 2022 remains stationary.



(a) **(b)**

Figure 6. (a) ACF Plot and (b) PACF Plot of Average Temperature of Banyuwangi Regency Differencing 12

The ACF plot in **Figure 6** shows that three lags leave the significant limits line, namely at lags 1 and 2 (non-seasonal lag) and lag 12 (seasonal lag). Meanwhile, the PACF plot shows that two lags leave the significant limits line, namely at lags 1 (non-seasonal lag) and 12 (seasonal lag). Thus, the model used in this study is a SARIMA $(p,d,q)(P,D,Q)^{12}$ model.

Based on the best model obtained, the concept of parsimony is used with several conditions that the model must meet; namely, the parameters in the model must be significant, have white noise residuals, be normally distributed, and have the smallest MSE (Mean Square Error) value. From several models that have been determined, it is necessary to test and compare one model with another to choose the best model [16].

The parameter significance test is conducted with a 95% confidence interval and the hypothesis of the test is as follows:

H_0 : The parameter is not significant in the model.

H_1 : The parameter is significant in the model.

The critical test area is to reject H_0 if the p-value < alpha (5%).

Table 4. Parameter Significance Test Results

Model		Parameter Significance		Conclusion
SARIMA $(0,0,1)(1,1,0)^{12}$	Probabilistic	SAR 12	0.000	Parameters are significant in the model
		MA 1	0.000	
SARIMA $(0,0,1)(0,1,1)^{12}$	Probabilistic	MA 1	0.000	Parameters are significant in the model
		SMA 12	0.000	
SARIMA $(0,0,1)(1,1,1)^{12}$	Probabilistic	SAR 12	0.548	Parameters are not significant in the model
		MA 1	0.000	
		SMA 12	0.000	

Model		Parameter Significance		Conclusion
SARIMA $(0,0,2)(1,1,0)^{12}$	Probabilistic	SAR 12	0.000	Parameters are significant in the model
		MA 1	0.000	
		MA 2	0.003	
SARIMA $(0,0,2)(0,1,1)^{12}$	Probabilistic	MA 1	0.000	Parameters are significant in the model
		MA 2	0.001	
		SMA 12	0.000	
SARIMA $(0,0,2)(1,1,1)^{12}$	Probabilistic	SAR 12	0.668	Parameters are not significant in the model
		MA 1	0.000	
		MA 2	0.003	
		SMA 12	0.000	
SARIMA $(1,0,0)(1,1,0)^{12}$	Probabilistic	AR 1	0.000	Parameters are significant in the model
		SAR 12	0.000	
SARIMA $(1,0,0)(0,1,1)^{12}$	Probabilistic	AR 1	0.000	Parameters are significant in the model
		SMA 12	0.000	
SARIMA $(1,0,0)(1,1,1)^{12}$	Probabilistic	SAR 12	0.000	Parameters are not significant in the model
		MA 1	0.675	
		SMA 12	0.000	
SARIMA $(1,0,1)(1,1,0)^{12}$	Probabilistic	AR 1	0.001	Parameters are not significant in the model
		SAR 12	0.000	
		MA 1	0.891	
SARIMA $(1,0,1)(0,1,1)^{12}$	Probabilistic	AR 1	0.000	Parameters are not significant in the model
		MA 1	0.055	
		SMA 12	0.000	
SARIMA $(1,0,1)(1,1,1)^{12}$	Probabilistic	AR 1	0.000	Parameters are not significant in the model
		SAR 12	0.162	
		MA 1	0.322	
		SMA 12	0.000	

Based on Table 4, parameter significance test results obtained from several models qualify to be selected as the best model. These models are the probabilistic models SARIMA $(0,0,1)(1,1,0)^{12}$, SARIMA $(0,0,1)(0,1,1)^{12}$, SARIMA $(0,0,2)(1,1,0)^{12}$, SARIMA $(0,0,2)(0,1,1)^{12}$, SARIMA $(1,0,0)(1,1,0)^{12}$, and SARIMA $(1,0,0)(0,1,1)^{12}$.

The next step is to test the white noise residual assumption to determine whether there is a correlation between the residuals with a mean equal to 0 and constant variance. The white noise residual test can be done by looking at the Ljung-Box significance value with the following test hypothesis.

$H_0 : \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (Residual data white noise).

H_1 : There is at least one $\rho_k \neq 0$; with $k = 1,2,3,\ldots k$ (Residual data is not white noise).

With a confidence interval of 95%, the critical test area is H_0 rejected if the Ljung-Box p-value < alpha (5%).

The following is presented in Table 5, the results of white noise residual assumption tests from several predetermined models.

Table 5. White Noise Residual Assumption Test Results

Model		*P-value* Lag				Conclusion
		12	24	36	48	
SARIMA $(0,0,1)(1,1,0)^{12}$	Probabilistic	0.074	0.029	0.010	0.053	Residual data is not white noise
SARIMA $(0,0,1)(0,1,1)^{12}$	Probabilistic	0.020	0.086	0.012	0.043	Residual data is not white noise
SARIMA $(0,0,2)(1,1,0)^{12}$	Probabilistic	0.189	0.072	0.045	0.126	Residual data is not white noise
SARIMA $(0,0,2)(0,1,1)^{12}$	Probabilistic	0.182	0.334	0.144	0.273	Residual data is white noise
SARIMA $(1,0,0)(1,1,0)^{12}$	Probabilistic	0.092	0.002	0.001	0.003	Residual data is not white noise
SARIMA $(1,0,0)(0,1,1)^{12}$	Probabilistic	0.276	0Ok Joey.328	0.093	0.261	Residual data is white noise

Based on **Table 5**, several models qualify to be selected as the best model. Models that fulfill the parameter significance test and the assumption of white noise residual data are the probabilistic SARIMA $(0,0,2)(0,1,1)^{12}$ and the probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$.

The next step is to test the assumption of normally distributed residuals and compare MSE values to determine the best model. The residual normality test uses the Kolmogorov-Smirnov test with a 95% confidence interval. If the residual data fulfill the normality assumption, then the model is appropriate to use. The hypothesis formulation of the residual normality test is as follows.

H_0 : Residual data is normally distributed.

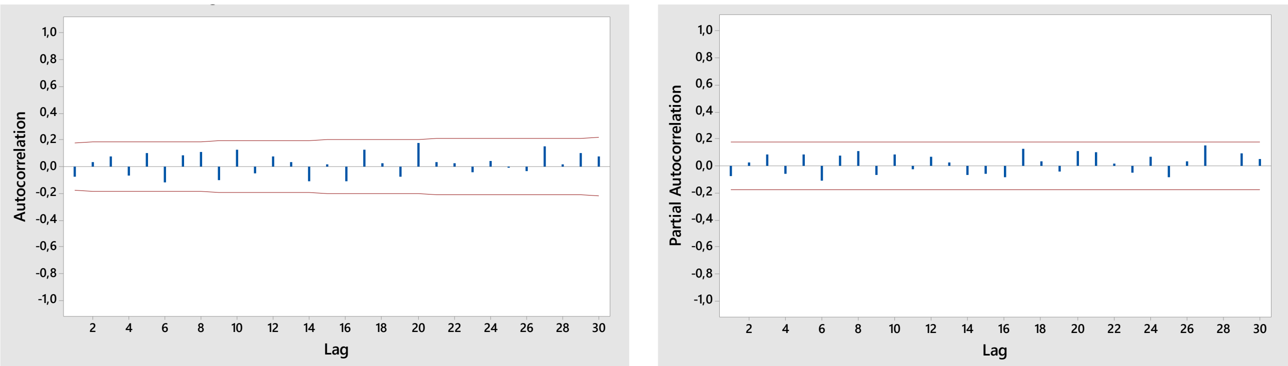
H_1 : Residual data is not normally distributed.

The critical region of this test is to reject H_0 if the p-value < alpha (5%). The MSE values and residual normality test results of the two selected models are presented in **Table 6**.

Table 6. MSE Value and Residual Normality Test Results

Model		MSE	P-value	Conclusion
SARIMA $(0,0,2)(0,1,1)^{12}$	Probabilistic	0.0005161	0.034	Residual data is not normally distributed
SARIMA $(1,0,0)(0,1,1)^{12}$	Probabilistic	0.0004967	0.059	Residual data is normally distributed

Based on **Table 6**, the results show that only the probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$ model meets the assumption test of normally distributed residuals. Furthermore, the homoscedasticity test is carried out on the model.



(a) (b)

Figure 7. (a) ACF Plot and (b) PACF Plot of Quadratic Residuals

From ACF and PACF plots in **Figure 7**, it is known that no lags go beyond the significant limit line. This indicates the presence of homoscedasticity, so the assumption of homoskedasticity has been met. Thus, the best model is obtained, namely the probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$ model or the ARSIMA model, because it has met the test requirements. The value of $p = 1,\ d = 0,\ q = 0,\ P = 0,\ D = 1,\ Q = 1$, and $S = 12$ so that the model **Equation (5)** of probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$ is obtained as follows.

$$\phi_1(B)\Phi_0(B^{12})(1-B)^0(1-B^{12})^1\dot{Z}_t = \theta_0(B)\Theta_1(B^{12})a_t$$

$$\phi_1(B)(1)(1)(1-B^{12})^1\dot{Z}_t = (1)\Theta_1(B^{12})a_t$$

$$\phi_1(B)(1-B^{12})\dot{Z}_t = \Theta_1(B^{12})a_t$$

$$(1-\phi_1 B)(1-B^{12})\dot{Z}_t = (1-\Theta_1 B^{12})a_t$$

$$(1-B^{12}-\phi_1 B+\phi_1 B^{13})\dot{Z}_t = (1-\Theta_1 B^{12})a_t$$

$$\dot{Z}_t - B^{12}\dot{Z}_t - \phi_1 B\dot{Z}_t + \phi_1 B^{13}\dot{Z}_t = a_t - \Theta_1 B^{12}a_t$$

$$\dot{Z}_t - \dot{Z}_{t-12} - \phi_1\dot{Z}_{t-1} + \phi_1\dot{Z}_{t-13} = a_t - \Theta_1 a_{t-12}$$

$$\dot{Z}_t = \phi_1\dot{Z}_{t-1} + \dot{Z}_{t-12} - \phi_1\dot{Z}_{t-13} + a_t - \Theta_1 a_{t-12} \quad (5)$$

$\dot{Z}_t$ is a form of transformation of the rounded value (λ) of 0.00 with the value of $\dot{Z}$ equal to e^{Z_t}. It is known that the coefficient value of parameter ϕ_1 is 0.5532 and the coefficient value of parameter Θ_1 is 0.8964 so that **Equation (6)** of the transformation model is obtained as follows.

$$\dot{Z}_t = 0.5532\,\dot{Z}_{t-1} + \dot{Z}_{t-12} - 0.5532\,\dot{Z}_{t-13} + a_t - 0.8964a_{t-12} \tag{6}$$

3.3 Forecasting Banyuwangi Average Temperature

Based on **Equation (6)**, forecasting can then be done to predict the average temperature of Banyuwangi Regency per month for period January 2023 to December 2023. Given that the results of the Box-Cox transformation produce a rounded value (λ) of 0.000 so that the results of forecasting or forecasting must be transformed into the form $\dot{Z}_t$ by calculating the exponential value of $\dot{Z}_t$ or e^{Z_t}. Then, MAPE value will be calculated to determine the average percentage of absolute error.

Table 7. Accuracy (MAPE) of Forecasting Results

Period	Actual Data (A_t)	Forecast (F_t)	$\frac{(A_t - F_t)}{A_t}$	$\left\lvert\frac{(A_t - F_t)}{A_t}\right\rvert$	APE
January 2023	27.20	27.09	0.004044	0.004044	0.404412%
February 2023	26.40	27.25	- 0.032197	0.032197	3.219697%
March 2023	27.40	27.62	- 0.008029	0.008029	0.80292%
April 2023	27.20	28.01	- 0.029779	0.029779	2.977941%
May 2023	27.40	27.90	- 0.018248	0.018248	1.824818%
June 2023	26.80	26.97	- 0.006343	0.006343	0.634328%
July 2023	25.70	26.16	- 0.017899	0.017899	1.789883%
August 2023	25.80	26.19	- 0.015116	0.015116	1.511628%
September 2023	26.20	26.77	- 0.021756	0.021756	2.175573%
October 2023	27.90	27.73	0.006093	0.006093	0.609319%
November 2023	28.50	28.09	0.014386	0.014386	1.438596%
December 2023	28.60	27.99	0.021329	0.021329	2.132867%
MAPE					**1.626832%**

Based on **Table 7**, a MAPE value of 1.626832% was obtained, which indicates that the forecasting model has a very high level of accuracy. According to Lewis and Colin David (1982) in Arwin et al. (2020), MAPE values below 10% are categorized as excellent forecasting **[18]**. However, despite this statistically impressive performance, such a low MAPE does not necessarily guarantee reliability across all practical contexts. In real-world situations—such as policy planning or disaster mitigation—external factors like the availability of real-time data, extreme climate variability, and infrastructure limitations can affect the model's overall effectiveness. Therefore, while the low MAPE reflects strong statistical accuracy, contextual evaluation remains essential to ensure the model's suitability for operational conditions. Compared with other methods using ARIMA, the best model is ARIMA (2,0,4) with a MAPE value of 3.76%, as seen in **Table 8**.

Table 8. Comparison between ARIMA and SARIMA Method

Method	MAPE
ARIMA (2,0,4)	3.76%
SARIMA $(1,0,0)(0,1,1)^{12}$	1.63%

Although this value is relatively small compared to the SARIMA model, the MAPE value of ARIMA is greater, showing that the SARIMA model is better at predicting the average temperature of Banyuwangi district. A similar study conducted on rainfall forecasting in Medan compared different forecasting methods and found that the SARIMA (1,0,1)(4,0,3)12 model achieved a MAPE of 2.93%, demonstrating high accuracy **[19]**. This further supports the effectiveness of the SARIMA model in time series forecasting. Changes in air temperature impact environmental damage, which affects the agricultural sector, which is very sensitive to the effects of climate change **[20]**. In addition, temperature changes can also affect tourist comfort, so it is necessary to plan open space processing by considering temperature factors **[21]**. Therefore, the results of this forecasting can be used as a reference to predict the average temperature of Banyuwangi Regency.

4. CONCLUSIONS

After identifying and stationary the data, the best model is obtained to predict the average temperature of Banyuwangi Regency, namely the probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$ model or ARSIMA model. The MSE value of the model is 0.0005161 with the equation $\dot{Z}_t = 0.5532\,\dot{Z}_{t-1} + \dot{Z}_{t-12} - 0.5532\,\dot{Z}_{t-13} + a_t - 0.8964a_{t-12}$. From this model, the average temperature forecasting of Banyuwangi Regency is obtained for the next year, namely in January 2023 - December 2023, with a MAPE of 1.63%. With an accuracy rate of 98.37%, it can be said that the probabilistic SARIMA $(1,0,0)(0,1,1)^{12}$ model is accurate in predicting the average temperature of Banyuwangi Regency in the future.

Furthermore, the model has practical implications for supporting climate change mitigation strategies and facilitating adaptive planning in vulnerable sectors such as agriculture and tourism, where timely and localized temperature predictions are essential for informed policy-making and operational decision-making. As a recommendation for future research, this model can be tested using more extended data periods or applied to other geographical regions to evaluate its consistency and robustness. In addition, these findings may serve as a foundation for local governments or stakeholders in designing policies more responsive to the dynamics of local climate conditions.

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