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TEMPERATURE DATA PREDICTION IN SOUTH SULAWESI PROVINCE USING SEASONAL-GENERALIZED SPACE TIME AUTOREGRESSIVE (S-GSTAR) MODEL

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ABSTRACT

Indonesia's distinct tropical climate is influenced by its geographic location near the equator and its complex topography, resulting in pronounced seasonal temperature patterns. This study examines the application of the Seasonal Generalized Space-Time Autoregressive (SGSTAR) model to forecast the average air temperature in four regions of South Sulawesi Province: North Luwu, Tana Toraja, Maros, and Makassar. The dataset comprises monthly average temperatures from January 2016 to October 2024, sourced from BMKG's online database. The analysis includes stationarity testing using the Augmented Dickey-Fuller (ADF) test, seasonal pattern identification with autocorrelation function (ACF), and formal seasonal tests such as QS, QS-R, and KW-R. Spatial weight matrices were constructed based on Euclidean distances between regions. The best model was selected based on Mean Square Error (MSE), Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), and adjusted R^2 criteria. The findings reveal that the seasonal GSTAR model with AR orders $(p = 4)$, $(ps = 6)$, and $(s = 12)$ is the optimal model. Evaluation indicates that the model achieves highly accurate forecast in for North Luwu and Makassar, with slightly less accurate forecast for Tana Toraja and Maros. This model effectively captures seasonal and spatio-temporal patterns in climate data. The study is expected to serve as a foundation for further development of seasonal GSTAR models for other climate datasets, supporting improved environmental planning and resource management.

Keywords : Seasonal GSTAR, Average Temperature, Forecasting

I. INTRODUCTION

Indonesia is geographically situated between the Indian and Pacific Oceans, as well as between the continents of Australia and Asia. It lies between 6° North Latitude and 11° South Latitude, and 95° East Longitude and 141° East Longitude. The country experiences two primary seasons, wet and dry, characteristic of its tropical climate [1] as described in [2]. According to the Meteorology, Climatology, and Geophysics Agency (BMKG), climate change refers to a phenomenon where the average weather conditions naturally shift or abnormalities occur, disrupting human activities and behaviors in a specific region. One of the key factors influencing climate change is temperature [3].

Air temperature is a measure of the degree of heat or cold at a specific location. It is influenced by several factors, including air humidity, solar radiation, and geographical conditions. Higher humidity levels indicate greater water vapor content, which can absorb heat energy and thus affect temperature fluctuations. According to [3], air temperature variations in Indonesia exhibit highly diverse daily and seasonal patterns, influenced by global phenomena such as El Niño and La Niña. High humidity levels in Indonesia suggest significant evaporation potential, which can substantially impact local temperature changes.

Air temperature in South Sulawesi Province is significantly influenced by its complex topographical variations, including coastal areas, lowlands, and mountain ranges extending from north to south. The province's geographic location near the equator results in high solar radiation throughout the year, leading to relatively stable average temperatures with seasonal variations. According to data from BMKG, the average temperature in South Sulawesi ranges between 24°C and 33°C, with the highest temperatures typically recorded during the dry season months, such as September to November [3].

Coastal regions such as Makassar and Pare-Pare tend to experience higher air temperatures compared to mountainous areas like Malino and North Toraja. This is attributed to the cooling effect at higher altitudes, coupled with increased air humidity. The high humidity levels, averaging 75–85%, also contribute to the perceived heat experienced by residents in lowland areas [4]. Additionally, global climate phenomena such as El Niño and La Niña influence temperature patterns in South Sulawesi. These phenomena can intensify or weaken the dry and rainy seasons, affecting daily average temperature fluctuations. According to annual reports, the highest temperature in the past five years was recorded in October 2023 in Makassar, reaching 36°C, while the lowest temperature was observed in the mountainous area of North Toraja in July 2023, at approximately 17°C [5].

Unstable temperature fluctuations can impact various aspects of people's lives. This is due to the dependence of daily activities on weather conditions, such as in agriculture, plantations, trade, transportation, and development. Therefore, information about weather conditions, including air temperature, is crucial to support the planning and implementation of various community activities [6]. Weather prediction, which involves forecasting air temperature, plays a crucial role in helping communities prepare for environmental changes. This process is typically carried out through forecasting methods that utilize historical data and mathematical models to predict future values or patterns. With this approach, communities and various economic sectors can make better decisions based on available information.

In statistics, time series analysis is a procedure used to predict future values based on past data [7]. One of the forecasting methods that can be applied is the Autoregressive Integrated Moving Average (ARIMA) method. This method has been widely used, including by [5] to forecast the annual average air temperature in Indonesia for the period 2022–2031. The best ARIMA model used for predicting the annual average air temperature in Indonesia was ARIMA (2,1,4), which indicated that the annual average air temperature in Indonesia for 2022 to 2031 is predicted to show a tendency to increase. However, this method cannot yet be used for forecasting data that integrates both time and location dimensions (spatio-temporal data).

One modeling technique for forecasting data that integrates both time and location dimensions (spatio-temporal data) is the Space-Time Autoregressive (STAR) model. This model was introduced by [8] for transportation data. However, STAR has limitations in handling locations with differing characteristics, leading to the development of a more flexible model, the Generalized Space-Time Autoregressive (GSTAR). GSTAR was developed by [9] allowing autoregressive and time series parameters to have heterogeneous values across different locations.

However, GSTAR is not capable of addressing seasonal patterns in multivariate time series data. To handle seasonal data, the Seasonal Generalized Space-Time Autoregressive (SGSTAR) model was developed, which integrates seasonal data with the Space-Time Autoregressive (GSTAR) predictor scheme to support the analysis of seasonal data patterns [10].

Previous studies have demonstrated the advantages of the Seasonal Generalized Space-Time Autoregressive (SGSTAR) method in data forecasting. [11] applied the Seasonal GSTAR model to predict quarterly rice yields in three districts in Central Java—Banyumas, Cilacap, and Kebumen—with results showing the model's superior forecasting performance. A similar study [12] also supports these findings, where the Seasonal GSTAR model yielded accurate forecasts. Forecasting the average air temperature has not previously been conducted using the SGSTAR method.

Based on these observations, this study aims to employ the Seasonal Generalized Space-Time Autoregressive (S-GSTAR) method to model and forecast air temperature data collected from four meteorological stations in South Sulawesi, namely the Andi Jemma Meteorological Station in North Luwu, the Toraja Meteorological Station in Tana Toraja, the Sultan Hasanuddin Meteorological Station in Maros, and the Paotere Maritime Meteorological Station in Makassar. In this study, the model’s location weighting is determined using the inverse distance weighting method.

II. METHODS

The data used in this study consists of secondary data obtained from the BMKG (Meteorology, Climatology, and Geophysics Agency) database website, accessible via the following link: https://dataonline.bmkg.go.id/. This secondary data includes information on temperature from January 2016 to October 2024, recorded by meteorological stations in four regions of South Sulawesi Province. The four regions, along with their respective station names, are as follows: North Luwu District (Andi Jemma), Maros District (Sultan Hasanuddin), Tana Toraja District (Toraja), and Makassar City (Maritim Paotere). The variable used in this study is the average temperature (°C), classified as ratio data. According to the Indonesian Dictionary (KBBI), the definition of average temperature (°C) refers to the average temperature observed over a continuous 24-hour period. The structure of the data used is as follows:

Table 1 : Structure of the Data

Year	Month	North Luwu	Tana Toraja	Maros	Makassar
2016	January	$Y_{1,1}$	$Y_{2,1}$	$Y_{3,1}$	$Y_{4,1}$
	February	$Y_{1,2}$	$Y_{2,2}$	$Y_{3,2}$	$Y_{4,2}$
	March	$Y_{1,3}$	$Y_{2,3}$	$Y_{3,3}$	$Y_{4,3}$
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	November	$Y_{1,11}$	$Y_{2,11}$	$Y_{3,11}$	$Y_{4,11}$
	December	$Y_{1,12}$	$Y_{2,12}$	$Y_{3,12}$	$Y_{4,12}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
2024	January	$Y_{1,49}$	$Y_{2,49}$	$Y_{3,49}$	$Y_{4,49}$
	February	$Y_{1,50}$	$Y_{2,50}$	$Y_{3,50}$	$Y_{4,50}$
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	September	$Y_{1,57}$	$Y_{2,57}$	$Y_{3,57}$	$Y_{4,57}$
	October	$Y_{1,58}$	$Y_{2,58}$	$Y_{3,58}$	$Y_{4,58}$

The data analysis in this study employs the Generalized Space-Time Autoregressive (GSTAR) method. The GSTAR model is a space-time model where the parameters are not required to have identical values for time and spatial dependencies. Since the data in this study exhibits seasonal patterns, the GSTAR model utilized is the seasonal GSTAR model. Mathematically, the GSTAR model for seasonal data patterns can be expressed in matrix notation as follows [13]:

$$\boldsymbol{Z}(t) = \sum_{k=1}^{p}\left[\boldsymbol{\Phi}^{s}{}_{k0}\boldsymbol{Z}(t-s) + \sum_{l=1}^{\lambda_p}\boldsymbol{\Phi}^{s}{}_{kl}\boldsymbol{W}^{(t)}\boldsymbol{Z}(t-s)\right] + \boldsymbol{e}(t) \quad (1)$$

where:

$\boldsymbol{\Phi}^{s}{}_{k0}$ =diag $\left(\phi_{k0}^{(1)}, \dots, \phi_{k0}^{(N)}\right)$ represents the parameter matrix for the seasonal period s

$\boldsymbol{\Phi}^{s}{}_{kl}$ =diag $\left(\phi_{kl}^{(1)}, \dots, \phi_{kl}^{(N)}\right)$ represents the spatial parameter matrix for the seasonal period

The GSTAR-Seasonal model assumes a linear relationship between the target variable and inputs in both spatial and seasonal dimensions, while also assuming that the data is stationary or has been processed to achieve stationarity. One limitation of this model is its dependence on data stationarity, which can complicate the analysis, especially for non-stationary data. Additionally, the model is sensitive to outliers and struggles to handle non-linear relationships, and it may require substantial computational time for large datasets. To address these issues, pre-processing techniques such as differencing are applied to ensure stationarity [14]. Therefore, an initial step involves testing for stationarity using the Augmented Dickey-Fuller (ADF) test. By using the ADF test, the GSTAR-Seasonal model ensures that the data used for analysis does not contain trends that could influence spatial and seasonal relationships, making the analysis more valid and reliable [15].

To detect seasonal patterns, the analysis begins with the Autocorrelation Function (ACF) test. The ACF test is useful for identifying periodic seasonal patterns by examining correlations at specific lags [16]. This is followed by the Q Statistics for Seasonality (QS) test, the Relative Q Statistics for Seasonality (QS-R) test, and the Kruskal-Wallis Relative Test for Seasonality (KW-R), which complement each other in examining seasonal patterns in the data analyzed using the GSTAR-Seasonal method. The QS test is based on the analysis of seasonal variation relative to total variation; if seasonal variation is significant compared to the total variation, the data exhibits seasonal patterns. The QS-R test calculates the strength of seasonality relative to trends or other components in the data. Meanwhile, the KW-R test compares the ranks of values within seasonal groups to determine the significance of seasonal patterns. Thus, the combination of these three tests enhances the accuracy of detecting seasonal patterns in spatial-seasonal data [14].

In the GSTAR-Seasonal model, spatial weights play a crucial role as they determine the strength of spatial relationships between locations and how seasonal patterns influence the variable being analyzed. The weights used in this study are based on Euclidean Distance, which is most suitable for continuous data, as is the case in this research. Additionally, the computation of Euclidean distance is computationally efficient, easy to implement, and provides intuitive interpretations, thus supporting the analysis of spatial-seasonal patterns in GSTAR-Seasonal [17].

The optimal model in GSTAR-Seasonal is identified through several evaluation metrics. MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) measure prediction accuracy, where smaller values indicate lower prediction errors. AIC (Akaike Information Criterion) is used to assess the balance between model fit and complexity, with models having lower AIC values considered more efficient. R^2 (Coefficient of Determination) evaluates how well the model explains the variation in the data, with values approaching 1 indicating a good fit. The combination of these four metrics ensures the selection of a model that is accurate, simple, and aligns well with the spatial and seasonal.

In this study, data analysis was conducted using R software, following these steps:

1. Data Collection: Gathering the required data.

2. Stationarity Check: Assessing the stationarity of the data both visually and through statistical testing using the Augmented Dickey-Fuller (ADF) test.
3. Seasonal Pattern Examination: Analyzing seasonal patterns using plots and the Autocorrelation Function (ACF), followed by formal tests such as QS, QS-R, and KW-R.
4. Spatial Weight Matrix Determination: Constructing the spatial weight matrix based on Euclidean distances.
5. Seasonal GSTAR Modeling: Splitting the data into training and testing sets with a 90:10 ratio.
6. Model Selection: Determining the AR order (p) and seasonal AR order (ps).
7. Optimal Model Identification: Selecting the optimal model based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Akaike Information Criterion (AIC), and Adjusted R^2.
8. Assumption Testing: Performing an independence test (Shapiro-Wilk) and residual normality test (Box-Ljung) for the optimal model.
9. Forecasting: Using the optimal model for predictions.
10. Prediction Comparison: Comparing the forecasted data with the testing data split during the initial modeling phase.
11. Evaluation: Assessing the forecast accuracy based on Mean Absolute Error (MAE) and RMSE.
12. Conclusion: Summarizing the findings.

III. RESULTS AND DISSCUSSION

3.1. Stationarity Tests

The initial step in time series data modeling is to ensure that the data is stationary. Stationarity can be observed visually or tested through statistical methods. Figure 1 illustrates the time series patterns of monthly average temperatures in four regions: North Luwu, Tana Toraja, Makassar, and Maros.

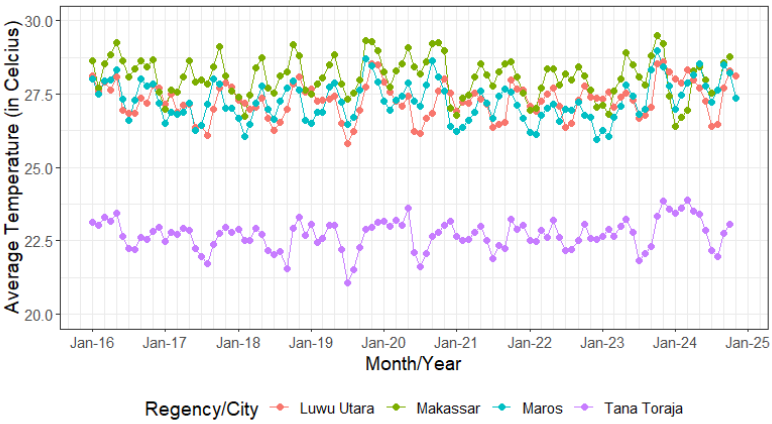

Figure 1. Time Series Plot of the Data

Visually, the temperature data for the four regions appear to fluctuate around a mean value without any significant trend, suggesting stationarity. However, the stationarity of the data can be more formally tested using the Augmented Dickey-Fuller (ADF) test. The results of the ADF test for these four regions are presented in Table 2.

Table 2: Test Result Augmented Dickey-Fuller

Regency/City	Dickey-Fuller	$p-value$
North Luwu	-5.0897	0.01000
Tana Toraja	-4.9850	0.01000
Maros	-3.3757	0.06225
Makassar	-3.7379	0.02455

Based on the test results, the data from North Luwu, Tana Toraja, and Makassar meet the stationarity assumption under the ADF test, with p-value < alpha, where α=0.05. However, the time series plots in Figure 1 indicate the presence of seasonal patterns. This observation is further supported by the Autocorrelation Function (ACF) plots for the four regions, as shown in Figure 2.

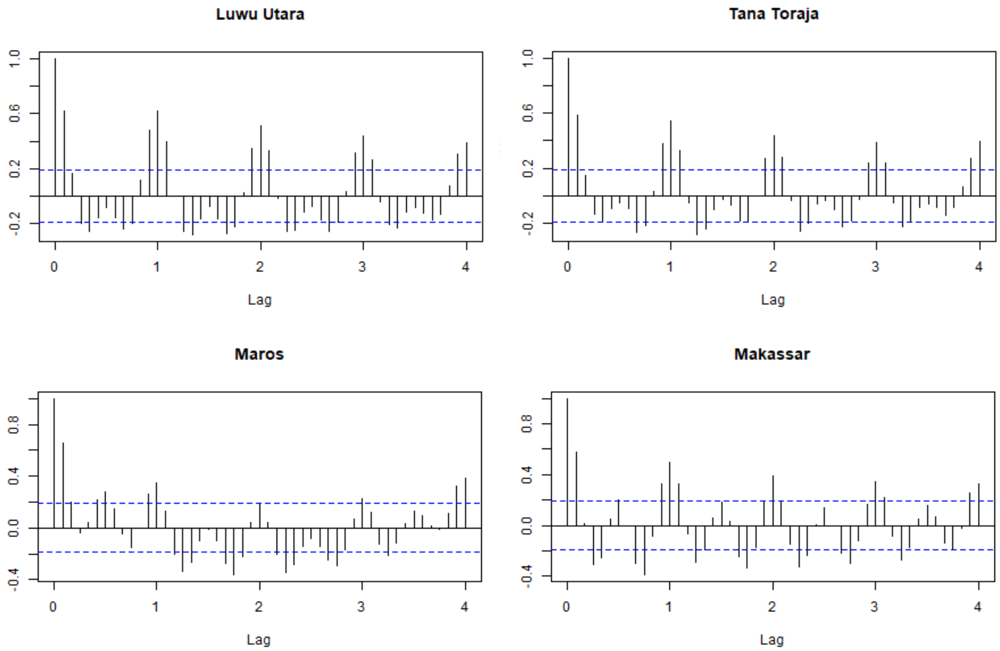

Figure 2: The ACF plot of the average temperature data for the four regions

Figure 2 illustrates a seasonal pattern with a lag of 12, indicating an annual seasonal cycle in the temperature data. This seasonal pattern can also be formally tested using the QS, QS-R, and KW-R tests. The results of these tests are presented in Table 3.

Table 3 : Seasonality Test Results

Regency/ City	QS $p - value$	QS-R $p - value$	KW-R $p - value$	Conclusion
North Luwu	4.66294e-15	2.52346e-07	2.21557e-05	Seasonal
Tana Toraja	9.82970e-11	4.29004e-06	8.13888e-06	Seasonal
Maros	3.10307e-13	1.23215e-04	4.72926e-06	Seasonal
Makassar	2.55051e-12	6.32308e-04	4.95879e-05	Seasonal

Based on the time series plot, ACF plot, and formal tests, it can be concluded that there is a seasonal pattern in the data. This seasonal pattern is not directly addressed, but will be handled using the Seasonal GSTAR model.

3.2. Spatial Weight Matrix

The initial step in GSTAR modeling is to determine the spatial weight matrix. The weights used are based on the distances between the regions. The reference distance is the distance from the central point of each region, expressed in terms of latitude and longitude, as shown in Table 4.

Table 4 : Central Coordinates of Each Regency/City

Regency/City	Latitude	Longitude
North Luwu	-2.550079	120.4616
Tana Toraja	-3.086729	119.8571
Maros	-5.016468	119.5745
Makassar	-5.133365	119.4082

The distances between the regions are calculated using the Euclidean distance and then standardized, resulting in the spatial weight matrix shown in Table 5.

Table 5 : Spatial Weight Matrix

Regency/City	North Luwu	Tana Toraja	Maros	Makassar
North Luwu	0	0.62572421	0.1929736	0.1813022
Tana Toraja	0.55547705	0	0.2302257	0.2142972
Maros	0.06562473	0.08819425	0	0.8461810
Makassar	0.06228285	0.08292756	0.8547896	0

3.3. GSTAR Modeling

The modeling process begins by dividing the data into training and testing datasets with a 90:10 ratio. The training data consists of 96 months, covering the period from January 2016 to December 2023, while the testing data includes the final 10 months, from January 2024 to October 2024. The model used is the Seasonal GSTAR model, which requires the determination of the AR order, seasonal AR order, and seasonal period. The seasonal period is 12 (months), as shown in the ACF plot in Figure

2. The optimal AR order (p) and seasonal AR order (ps) are determined based on the MSE, RMSE, AIC, and R² values. Table 6 presents the 5 combinations of orders with the best evaluation metrics.

Table 6 : Optimal orders for Seasonal-GSTAR

p	ps	MSE	RMSE	AIC	R^2
5	6	0.0061	0.0734	0.0153	0.9860
4	6	0.0092	0.0886	0.0212	0.9800
11	5	0.0105	0.1010	0.0255	0.9690
10	5	0.0134	0.1150	0.0308	0.9590
9	5	0.0194	0.1380	0.0422	0.9430

Based on Table 6, the optimal order for this model is $p = 5$ and $ps = 6$. However, this model fails the residual independence test and, therefore, is not used. As an alternative, the second-best model is selected, which has $p = 4$ and $ps = 6$. The residuals of this model meet the assumptions of independence and normality, as shown in Table 7.

Table 7 : Results of Residual Independency and Normality Tests

Regency/City	Shapiro-Wilk ($p - value$)	Box-Ljung ($p - value$)
North Luwu	0.9136	0.0197
Tana Toraja	0.1524	0.5017
Maros	0.6594	0.2521
Makassar	0.9523	0.0129

Therefore, it can be concluded that the best model is the Seasonal GSTAR model with $p = 4$, $ps = 6$, and $s = 12$.

3.4. Forecasting

The optimal model is then used to forecast the average temperature data for the next 10 months. The forecasted data is presented in Table 8.

Table 8 : Forecasting Results

Month/Year	North Luwu	Tana Toraja	Maros	Makassar
January 2024	27.41628	23.20691	26.95868	28.36912
February 2024	26.71531	23.18310	28.06063	26.09792
March 2024	26.89794	22.64325	26.28342	29.01481
April 2024	28.77019	23.82168	29.35990	26.93700
May 2024	28.18233	21.59118	25.57413	31.21122
June 2024	26.48291	23.22051	30.16095	24.01340
July 2024	24.40187	22.09888	23.33281	31.27521
August 2024	28.60239	22.85327	32.96740	23.93573
September 2024	28.15926	18.52064	19.62856	35.61418
October 2024	29.61264	27.71522	37.83332	20.43904

The forecasted data in Table 8 is then compared with the test data that was separated at the beginning of the modelling process. The evaluation results, including MAE and RMSE values, indicate the closeness between the forecasted results and the test data.

Table 9 : Evaluation of Forecasting Results

Regency/City	MSE	RMSE	MAPE
North Luwu	1.56	1.25	4.1%
Tana Toraja	18.00	4.25	12.7%
Maros	23.40	4.84	13.0%
Makassar	4.55	2.13	6.2%

Table 9 demonstrates that the forecast accuracy varies across regions. North Luwu exhibits the highest forecast accuracy, as indicated by the lowest MSE of 1.56 and RMSE of 1.25. Makassar has relatively low error values, with an MSE of 4.55 and an RMSE of 2.13. Tana Toraja and Maros have higher errors, with RMSEs of 4.25 and 4.84, respectively, indicating that the forecasted values deviate by approximately 4 to 5 degrees Celcius from the actual temperatures.

It is important to note, as shown in Figure 1, that the temperature ranges differ across regions, particularly for Tana Toraja. To provide additional context, MAPE values were also calculated for each region. As shown in Table 9, the MAPE values for Tana Toraja and Maros are both below 20%, which is still considered to reflect good accuracy, albeit not as highly accurate as the forecasted results for North Luwu and Makassar.

IV. CONCLUSION

The average temperature data from four regencies/cities in South Sulawesi Province exhibits monthly seasonal components, making the seasonal GSTAR model a suitable choice. In this study, the optimal model obtained is GSTAR with AR orders $p = 4$, $ps = 6$, and $s = 12$. Although this model is not the best in terms of MSE, RMSE, AIC, or R^2, it was selected because it satisfies residual assumptions, ensuring reliable interpretation and forecasting. Model fitting on the training data resulted in an MSE of 0.0092 and an RMSE of 0.0886, indicating the model's ability to capture temperature patterns with deviations of less than 1°C, which is sufficient for practical applications. Forecasting accuracy varies across regions, with North Luwu and Makassar exhibit the most accurate forecasts, while Tana Toraja and Maros show slightly lower accuracy, with MAPEs of 12.7% and 13.0%, respectively. This research serves as a foundation for developing seasonal GSTAR models for other climate datasets, integrating relevant variables, and achieving more accurate modeling to support planning across various sectors, such as agricultural planning, disaster mitigation, and climate policy development.

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