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MODELING OF VECTOR AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND GENERALIZED SPACE TIME AUTOREGRESSIVE INTEGRATED MOVING AVERAGE BASED ON DISTANCE INVERSION MATRIX AND CROSS-CORRELATION NORMALIZATION IN THE CASE OF AIR TEMPERATURE IN WEST NUSA TENGGARA

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Abstract- Forecasting predicts future events by analyzing historical data. The VARIMA model is used for multivariate time series forecasting, incorporating multiple variables from previous periods. In West Nusa Tenggara, air temperature significantly influences agricultural production and exhibits spatial variations, leading to differences in model parameters across locations. The GSTARIMA model accounts for both spatial and temporal dependencies, allowing parameters to vary by location. This study compares the VARIMA and GSTARIMA models, utilizing inverse distance weighting and cross-correlation matrices to determine the optimal approach for forecasting air temperature. GSTARIMA requires fewer parameters than VARIMA. The results indicate that the GSTARIMA $(3,1,1)^1$ model with inverse distance weighting is the most effective, achieving the lowest RMSE of 2.821 while meeting feasibility criteria. Forecasts from December 2024 to June 2025 closely align with out-of-sample data, demonstrating high accuracy.

Index Terms- Statistics, VARIMA, GSTARIMA, Temperature Forecasting.

I. INTRODUCTION

Forecasting predicts future conditions using past data. This study focuses on improving air temperature forecasting in West Nusa Tenggara (NTB), as one of the main components in the agricultural sector, air temperature plays a vital role in advancing economic growth and food crop production in Indonesia, especially in the West Nusa Tenggara region, known as an agricultural country because the majority of its population makes a living in the agricultural sector and farming. Air temperature is an important variable in weather forecasting, helping to predict rain, storms, and other extreme phenomena. Helping mitigate disasters such as heat waves, forest fires, and other extreme weather [1]

Spatio temporal interactions are crucial for understanding temperature variations. Spatial dependency analysis studies how values at one location are affected by nearby locations based on geography. Traditional models like VARIMA handle multivariate time series but do not incorporate this spatial dependency, limiting their ability to capture temperature variations across different regions. In temperature forecasting, spatial dependency analysis is essential because temperature patterns are not only influenced by temporal trends but also by geographic factors such as altitude, proximity to water bodies, and regional climate differences. Without accounting for spatial dependencies, predictions may overlook important location-based influences, reducing forecasting accuracy [2] [3]. The GSTARIMA model incorporates spatial weighting matrices, providing a more comprehensive approach to regional temperature forecasting [4] [5]. Recent data from NTB meteorological stations in November 2023 show consistently high temperatures between 31°C to 37°C. Zainuddin Abdul Madjid Station in Lombok recorded 31°C to 33°C, Sultan Muhammad Kaharuddin Station in Sumbawa observed 33°C to 37°C, and Sultan Muhammad Salahuddin Station in Bima noted 33°C to 36°C. These patterns highlight the importance of accurate forecasting models to address risks such as drought and reduced agricultural productivity.

To analyze and forecast air temperature variations, this study employs the VARIMA and GSTARIMA models. VARIMA is widely used for multivariate time series forecasting, making it suitable for capturing temporal dependencies in climate data. However, it does not account for spatial relationships, which are critical in geographically distributed data. GSTARIMA extends this approach by incorporating spatial dependencies, making it more effective for modeling temperature variations influenced by geographic factors. The selection of these models is based on their ability to handle both time series structures and spatial correlations, ensuring a more comprehensive temperature forecasting approach in NTB.

This research employs the Ordinary Least Squares (OLS) method for parameter estimation, building on previous studies that demonstrate the advantages of incorporating spatial effects [6]. Integrating VARIMA and GSTARIMA captures both temporal and spatial patterns, enhancing forecasting accuracy. This combined approach offers valuable insights for climate resilience, sustainable development, and effective risk management in NTB. This comparison aims to identify the model best suited to capture the spatio temporal dynamics of air temperature in West Nusa Tenggara

IDENTIFY, RESEARCH AND COLLECT IDEA

2.1 Time Series Analysis

A sequence of observations forms a time series model when it satisfies two criteria [7]:

1. In this time series analysis, observations at each time point t must satisfy two conditions. First, the time intervals between indices t are consistent and uniform, such as in data recorded daily over a one-year period
2. A relationship exists between observations Z_t and Z_{t+k} where the time difference between these observations is a multiple of the time interval Δ_t referred to as lag k. This

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relationship reflects how present values are connected to future values, depending on the specific data used, whether it pertains to economic trends, weather patterns, or other domains

2.2 Correlation Test

The Pearson Product Moment correlation coefficient can be computed using the following formula [7].

$$r = \frac{n\sum_{j=1}^{n}\sum_{i=1}^{n} Z_i Z_j - \sum_{i=1}^{n} Z_i \sum_{j=1}^{n} Z_j}{\sqrt{n\sum_{i=1}^{n} Z_i^2 - \left(\sum_{i=1}^{n} Z_i\right)^2}\sqrt{n\sum_{j=1}^{n} Z_j^2 - \left(\sum_{j=1}^{n} Z_j\right)^2}}$$

The formula represents the Pearson correlation coefficient (r), which measures the linear relationship between two variables in a time series. It helps identify dependencies between observations at different time points.

a. If r is close to 1, it indicates a strong positive correlation.
b. If r is close to -1, it indicates a strong negative correlation.
c. If r is close to 0, it suggests no significant linear relationship.

The steps for performing a correlation test are as follows [3].

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$$

Reject H_0 if $|t| \geq t_{\alpha,n-2}$ or if the $p-\text{value} \leq \alpha$

2.3 Regional Heterogeneity Test Using the Gini Index

The following are the steps to test regional heterogeneity using the Gini Index [4].

Test Statistic: $G = 1 + \frac{1}{n} - \frac{2}{n^2\bar{Z}_i}\sum_{i=1}^{N} Z_i$

The null hypothesis (H_0) is rejected if the Gini Index value G is high, indicating a significant level of inequality. However, a Gini Index G ≥ 1, does not always imply heterogeneity but rather an extreme level of disparity. Therefore, a deeper discussion of regional heterogeneity is necessary to provide a more nuanced interpretation.

Data Stationarity

Stationarity implies that data does not exhibit upward or downward trends over time.

2.4 Variance Stationarity

According to [8] data is considered stationary in variance if the transformation parameter (λ) is equal to or close to one.
The Box-Cox transformation parameter (λ), introduced by [9], is commonly used to achieve variance stationarity, as shown in Equation 2.4:

$$\mathbf{Z_t^{(\lambda)}} = \frac{\mathbf{Z_t^{(\lambda)} - 1}}{\boldsymbol{\lambda}}$$

2.5 Mean Stationarity

Data is considered stationary in mean if the autocorrelation values for the first three lags do not exceed $\pm\frac{2}{\sqrt{n}}$.. If this condition is not met, differencing should be applied until stationarity is achieved. The first-order differencing (d = 1) is expressed as [10].

$$\Delta Z_t = Z_t - Z_{t-1}$$

The hypotheses are:
$H_0 : \Phi^* \geq 0$ (data is not stationary in mean)
$H_1 : \Phi^* < 0$ (data is stationary in mean)
Test statistic:

$$\tau = \frac{\hat{\Phi}^*}{Se(\hat{\Phi}^*)}$$

2.6 Identifying VARIMA Model

According to [11] the sample matrix correlation function for a time series vector with n observations $Z_1, Z_2, \ldots, Z_n$ is calculated as:

$$\hat{\boldsymbol{\rho}}(k) = [\hat{\rho}_{ij}(k)]$$

In this context, $\hat{\rho}_{ij}(k)$ denotes the sample cross-correlation between the i-th and j-th variables at a lag of k

$$\hat{\rho}_{ij}(k) = \frac{\sum_{t=1}^{n-k}(Z_{i,t} - \bar{Z}_i)(Z_{j,t+k} - \bar{Z}_j)}{\sqrt{\sum_{t=1}^{n}(Z_{i,t} - \bar{Z}_i)^2 \sum_{t=1}^{n}(Z_{j,t} - \bar{Z}_j)^2}}$$

The formula for the partial matrix correlation function is [12]:

$$\Phi_{kk} = \frac{Cov[(Z_t - \hat{Z}_t),(Z_{t+k} - \hat{Z}_{t+k})]}{\sqrt{var(Z_t - \hat{Z}_t)}\sqrt{var(Z_{t+k} - \hat{Z}_{t+k})}}$$

where $\hat{Z}_t$ and $\hat{Z}_{t+k}$ are linear regression estimates with minimal Mean Squared Error (MSE). MPACF is used to identify the VAR model, where a cutoff at lag p suggests a VAR(p) model.

2.7 Vector Autoregressive Integrated Moving Average (VARIMA) Model

The VARIMA (p, d, q) model, where "p" stands for the order of autoregression and "q" represents the moving average order, is defined as [11], [13]:

$$\boldsymbol{\Phi}_p(B)\mathbf{D}(B)\mathbf{Z_t} = \boldsymbol{\Theta}_q(B)\mathbf{a}_t$$

Ordinary Least Squares (OLS) is employed to estimate VARIMA parameters. Using Ordinary Least Squares (OLS) in time series analysis requires verifying key assumptions. Autocorrelation can bias estimates, non-stationarity may lead to spurious results, and heteroskedasticity affects error reliability. To address these issues, researchers should conduct stationarity tests (ADF, KPSS), apply data transformations (differencing, log), or use alternative models (ARIMA, VAR, GSTARIMA) if needed. Ensuring these assumptions are met is crucial for valid and interpretable results Alternatively, the smallest Akaike Information Criterion (AIC) value is used to select the appropriate lag length, given by:

$$AIC = m\log\left(\frac{SSE}{m}\right)$$

2.8 Spatial Weight Matrix

In GSTARIMA modeling, spatial weights can be defined as:

Inverse Distance Weight

Inverse Distance Weighting (IDW) is chosen in the GSTARIMA model because it naturally reflects spatial relationships, where closer locations have stronger influences. It is simple to implement, does not require complex parameter estimation, and aligns well with GSTARIMA's structure. Compared to other weighting methods, such as binary contiguity or spatial weight matrices, IDW provides a smooth distance-based weighting approach, making it more suitable for geospatial data like temperature. However, a comparison with alternative methods could further justify its selection [13].

$$d_{ij} = d_{ji} = \sqrt{(x_i(u_i) - x_j(u_j))^2 + (x_i(v_i) - x_j(v_j))^2}$$

The normalized inverse distance weight for each region is computed as [7].

$$w_{ij} = \begin{cases} \frac{w_{ij}}{\sum_{j=1}^{n} w_{ij}}, i \neq j \\ 0, \quad i = j \end{cases}$$

2.9 Cross-Correlation Normalized Weight

Unlike distance-based weighting, cross-correlation weights depend on time lags between observations. The cross-correlation at lag k for regions i and j is:

$$\rho_{ij}(k) = \frac{\gamma_{ij}(k)}{\sigma_i \sigma_j}, k = 0, \pm 1, \pm 2, \ldots$$

where $\gamma_{ij}(k)$ represents cross-covariance, and σ_i and σ_j are standard deviations. Sample cross-correlation is estimated as [11], [14]:

$$r_{ij}(k) = \frac{\sum_{t=k+1}^{n} [Z_i(t) - \bar{Z}_i][Z_j(t-k) - \bar{Z}_j]}{\sqrt{(\sum_{t=1}^{n} [Z_i(t) - \bar{Z}_i]^2)\left(\sum_{t=1}^{n} [Z_j(t) - \bar{Z}_j]^2\right)}}$$

Weights are determined by normalizing the correlation values [14]:

$$w_{ij} = \frac{r_{ij}(k)}{\sum_{k \neq i} |r_{ik}(k)|}, i \neq j$$

For $i \neq j, k = 1, \ldots p$ the weights satisfy $\sum_{i \neq j} |w_{ij}| = 1$.

II. WRITE DOWN YOUR STUDIES AND FINDINGS

A. Bits and Pieces together

This research aims to model and forecast monthly average air temperature in West Nusa Tenggara Province using two multivariate time series methods: Vector Autoregressive Integrated Moving Average (VARIMA) and Generalized Space-Time Autoregressive Integrated Moving Average (GSTARIMA). The study utilizes secondary data obtained from the Meteorological, Climatological, and Geophysical Agency (BMKG) of Indonesia. The dataset comprises monthly average air temperature from January 2017 to November 2024 recorded at three meteorological stations: Sultan Muhammad Kaharuddin Station (Sumbawa), Zainuddin Abdul Madjid Station (Lombok), and Sultan Muhammad Salahuddin Station (Bima), yielding a total of 95 data points per station.

The dataset was partitioned into two segments:

- In-sample data (January 2017 – April 2023, 76 observations), used for model construction.
- Out-of-sample data (May 2023 – November 2024, 19 observations), used for model validation and forecasting evaluation.

2.10 Generalized Space Time Autoregressive Integrated Moving Average (GSTARIMA) Model

Key aspects of the model are described by [15].

$$\nabla \mathbf{Z_t} = \sum_{k=1}^{p} \sum_{l=0}^{\lambda_p} \mathbf{\Phi}_{kl} \mathbf{W}^{(l)} (\mathbf{1} - \mathbf{B})^{\mathbf{d}} \nabla \mathbf{Z_{t-k}} - \sum_{k=1}^{q} \sum_{l=0}^{m_q} \mathbf{\Theta_{kl}} \mathbf{W}^{(l)} \mathbf{e}_{t-k} + \mathbf{e}_t \quad (12)$$

2.11 Model Diagnostic Check

Model diagnostic testing evaluates model suitability for forecasting. (13)

White Noise Test

This test checks if residuals are uncorrelated with zero mean and constant variance, using the Ljung-Box statistic [16].

$$Q = n(n+2) \sum_{k=1}^{K} \frac{\rho_k^2}{n-k} \quad (14)$$

Multivariate Normality Test

Beyond independence, residual normality is tested using the Mahalanobis distance [17]:

$$D^2 = (x_i - me) C^{-1} (x_i - me)^T \quad (15)$$

2.12 Model Selection

The best model is determined by forecasting accuracy, using RMSE as the evaluation criterion. The model with the lowest RMSE is deemed the most accurate [7].

$$RMSE = \sqrt{MSE} \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left((Z_{i(t)} - \hat{Z}_{i(t)}) \right)^2} \quad (16)$$

To begin, descriptive statistical analysis was conducted to understand the distribution, central tendency, and variability of air temperature at each station. Spatial characteristics of the data were evaluated through Moran's I statistic, which tested for the presence of spatial autocorrelation among the stations. Furthermore, regional heterogeneity tests were performed to examine the degree of variability in temperature behavior across different locations.

The GSTARIMA model required the construction of spatial weight matrices. Two types of weights were used:

1. Distance inversion weight, calculated based on the reciprocal of the geographic distance between stations.
2. Cross-correlation normalization, based on the temporal cross-correlation between temperature series from different stations.

Prior to model estimation, the stationarity of the data was verified. Stationarity in variance was assessed using the Box-Cox transformation. If the estimated transformation parameter (λ) was close to one, the data were considered variance-stationary. If not, transformation was applied. Stationarity in mean was evaluated using Augmented Dickey-Fuller (ADF) test and Modified

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Autocorrelation Function (MACF) plots. If non-stationarity was detected, differencing was applied until stationarity was achieved.
The VARIMA model was developed following these steps:

- Selection of optimal model order based on Akaike Information Criterion (AIC).
- Parameter estimation using maximum likelihood estimation.
- Model diagnostics including white noise test on residuals and multivariate normality test using Mahalanobis distance (D^2).

For the GSTARIMA model, the spatial order was fixed at one, and the temporal order followed the optimal order determined from the VARIMA model. Parameters were estimated using the Ordinary Least Squares (OLS) method. Residual diagnostics were again performed using the Ljung-Box test for white noise and D^2 for multivariate normality.

After modeling, both VARIMA and GSTARIMA were used to forecast out-of-sample air temperature values. Forecast accuracy was assessed by calculating the Root Mean Square Error (RMSE) for each model. The model with the lowest RMSE was selected as the best-performing model. Finally, the results were interpreted to evaluate the temporal and spatial behavior of air temperature across the three stations.

Estimation of Parameters Φ and Θ using Ordinary Least Squares (OLS)

According to [3], [13] used OLS for parameter estimation in VARIMA and GSTARIMA models. The GSTARIMA (3,1,1) model, with p=3 and q=1, follows the general form of VARIMA (3,1,1) with first differencing.

The linear regression model corresponding to VARIMA and GSTARIMA (3,1,1) is:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \quad (21)$$

Thus, the estimated value of $\boldsymbol{\beta}$ is obtained as follows:

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X_i}'\mathbf{X_i})^{-1}(\mathbf{X_i}'\mathbf{Y_i}) \quad (22)$$

Descriptive Statistics

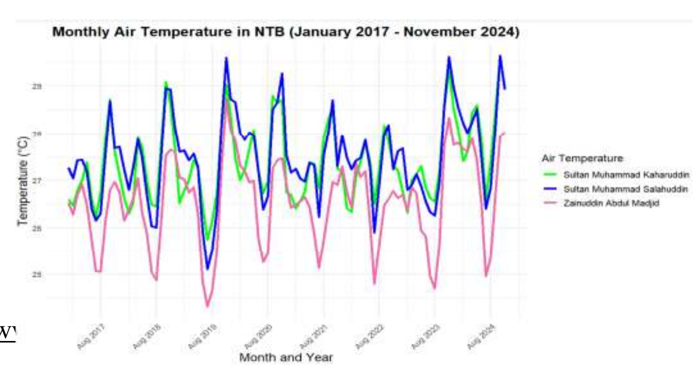

Figure 1. Air Temperature Graph for 3 BMKG Stations in NTB Province

Table 2. Descriptive Analysis of Air Temperature at Three BMKG Stations in NTB

	Sultan Muhammad Kaharuddin	Sultan Muhammad Salahuddin	Zainuddin Abdul Madjid
Average	27,38	26,54	27,50
StandardDeviation	0,83	0,93	0,92
Minimum	25,75	24,32	25,10
Maximum	29,58	28,74	29,63
Range	3,83	4,42	4,53

Data Correlation Test

The underlying assumption of the GSTARIMA model is the correlation between observation areas [7].

Table 3. Air Temperature Correlation Coefficient between BMKG Stations

	SMK	ZAM	SMS
SMK	1	0,6831	0,8692
ZAM	0,6831	1	0,9080
SMS	0,9080	0,8692	1

Regional Heterogeneity Test

a. Heterogeneity Test for Sultan Muhammad Kaharuddin Station

Test Statistic:

$$G = 1 + \frac{1}{n} - \frac{2}{n^2\overline{Z}_i}\sum_{i=1}^{N} Z_i = 1 + \frac{1}{285} - \frac{2}{(285)^2 \times (27{,}37853)} \times (2600{,}96) = 1{,}0011696 \approx 1{,}00117$$

The test region indicates rejecting H□ if G ≥ 1. With a Gini index value of 1.00117, H□ is rejected.

b. Heterogeneity Test for Zainuddin Abdul Madjid Station

Test Statistic:

$$G = 1 + \frac{1}{n} - \frac{2}{n^2\overline{Z}_i}\sum_{i=1}^{N} Z_i = 1 + \frac{1}{285} - \frac{2}{(285)^2 \times (26{,}54389)} \times (2521{,}67) = 1{,}0011696 \approx 1{,}00117$$

The test region indicates rejecting H□ if G ≥ 1. With a Gini index value of 1.00117, H□ is rejected.

c. Heterogeneity Test for Sultan Muhammad Salahuddin Station

Test Statistic:

$$G = 1 + \frac{1}{n} - \frac{2}{n^2\overline{Z}_i}\sum_{i=1}^{N} Z_i = 1 + \frac{1}{285} - \frac{2}{(285)^2 \times (27{,}49568)} \times (2612{,}09) = 1{,}0011696 \approx 1{,}00117$$

The test region indicates rejecting H□ if G ≥ 1. With a Gini index value of 1.00117, H□ is rejected.

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Time Series Plot Identification

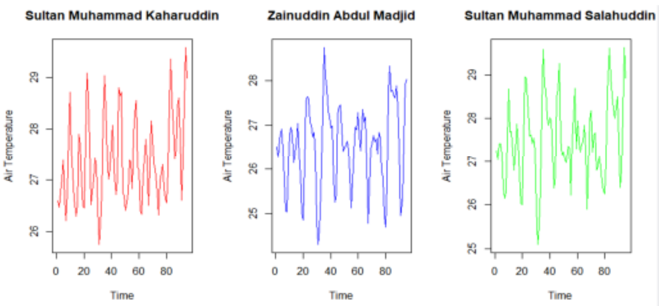

Figure 2. Time Series Plot of Three Regions

Based on Figure 2, the time series plots suggest that the air temperature data may not be stationary in both mean and variance. The fluctuations indicate possible trends or seasonal patterns, meaning the average temperature is not constant over time. Additionally, the spread of variations appears uneven, suggesting changes in variance. This non-stationarity can affect the accuracy of forecasting models like VARIMA and GSTARIMA. To address this, statistical tests such as the ADF or KPSS test should be conducted, and transformations like differencing or variance stabilization may be applied to ensure stationarity before modeling.

Data Stationarity

Stationarity in Variance

Table 4. Box-Cox Test Results

Station	Lambda Value (λ)
SMK	-0,999924
ZAM	1,999924
SMS	-0,999924

Table 5. Box-Cox Test After Transformation

Station	Lamda Value (λ)
SMK	1
ZAM	1
SMS	1

Stationarity in Mean

Table 6. Augmented Dickey-Fuller (ADF) Test Results

Station	Dickey Fuller	p-value	Decision	Conclusion
SMK	-3,346	0,07	Accept H_0	Not Stationary
ZAM	-4,599	0,01	Reject H_0	Stationary
SMS	-3,439	0,06	Accept H_0	Not Stationary

Table 7. Augmented Dickey Fuller test after differencing

Station	Dickey Fuller	p-value	Desicion	Conclusion
SMK	-5,263	0,01	Reject H_0	Stationary
ZAM	-4,599	0,01	Reject H_0	Stationary
SMS	-5,344	0,01	Reject H_0	Stationary

The Augmented Dickey-Fuller test at a 5% significance level shows all stations are stationary. Sultan Muhammad Kaharuddin, Zainuddin Abdul Madjid, and Sultan Muhammad Salahuddin Stations have Dickey-Fuller values of -5.263, -4.599, and -5.344, with p-values of 0.01. Since p-values are below 0.05, the null hypothesis is rejected. First differencing produces a VAR I(1) MA model.

Identification of VARIMA Model

Schematic Representation of Cross Correlations											
Variable/Lag	0	1	2	3	4	5	6	7	8	9	10
Kaharuddin	+++	.++	-..	---	...	...	+++	...	---	---	---
Madjid	+++	.++	-.-	---	---	...	+..	...	.-.	---	...
Salahuddin	+++	.+.	-..	---	--.	...	++.	...	.-.	---	...
+ is > 2*std error, - is < -2*std error, . is between											

Figure 3. MACF Plot of Air Temperature Data for the Three Stations

Schematic Representation of Partial Cross Correlations										
Variable/Lag	1	2	3	4	5	6	7	8	9	10
Kaharuddin	...	...	-..	..+	..+	...	..+	...	...	...
Madjid	..+	-..	--.	.-.	.-.	+..	...	...	...	...
Salahuddin	.+.	..-	.+.	...	-..	...	...	...	...	...
+ is > 2*std error, - is < -2*std error, . is between										

Figure 4. MPACF Plot of Air Temperature Data at the Three Stations

Table 8. AIC Values

Minimum Information Criterion Based on AIC					
Lag	**MA 0**	**MA 1**	**MA 2**	**MA 3**	**MA 4**
AR 0	-4,879	-5,082	-4,929	-4,825	-4,625
AR 1	-5,072	-5,435	-5,274	-5,148	-4,986
AR 2	-5,126	-5,470	-5,309	-5,362	-5,199
AR 3	-5,510	**-5,919**	-5,754	-5,719	-5,566
AR 4	-5,657	-5,841	-5,776	-5,554	-5,310

Table 9. Parameter Estimation of VARIMA Model (3,1,1)

Parameter	Estimasion	p-value	Parameter	Estimasion	p-value
Φ_{11}^{1}	0,308	0,251	Φ_{21}^{3}	-1,04720	0,006
Φ_{12}^{1}	-0,714	0,208	Φ_{22}^{3}	-1,07387	0,000
Φ_{13}^{1}	0,624	0,303	Φ_{23}^{3}	1,82246	0,000
Φ_{11}^{2}	-0,56905	0,093	Θ_{21}^{1}	0,03026	0,955

Φ_{12}^{2}	-0,83567	0,013	Θ_{22}^{1}	-1,20999	0,072
Φ_{13}^{2}	1,05831	0,040	Θ_{23}^{1}	1,81913	0,025
Φ_{11}^{3}	-0,81968	0,011	Φ_{31}^{1}	0,03375	0,933
Φ_{12}^{3}	-0,97532	0,000	Φ_{32}^{1}	-1,00295	0,173
Φ_{13}^{3}	1,26340	0,003	Φ_{33}^{1}	1,56548	0,040
Θ_{11}^{1}	1,72695	0,000	Φ_{31}^{2}	-0,94942	0,042
Θ_{12}^{1}	-1,32398	0,020	Φ_{32}^{2}	-1,25153	0,004
Θ_{13}^{1}	-0,15180	0,822	Φ_{33}^{2}	1,70614	0,010
Φ_{21}^{1}	-0,42352	0,251	Φ_{31}^{3}	-0,86636	0,052
Φ_{22}^{1}	-1,10068	0,103	Φ_{32}^{3}	-1,18847	0,001
Φ_{23}^{1}	2,13886	0,004	Φ_{33}^{3}	1,75599	0,002
Φ_{21}^{2}	-1,11017	0,008	Θ_{31}^{1}	0,37204	0,381
Φ_{22}^{2}	-1,41229	0,000	Θ_{32}^{1}	-1,76519	0,010
Φ_{23}^{2}	2,05075	0,0012	Θ_{33}^{1}	1,89823	0,0171

Residual White Noise Assumption

H_0 : $\rho_1 = \rho_2 = \cdots = \rho_K = 0$ (Residuals are white noise (not correlated))

H_1 : There is at least one $\rho_j \neq 0, j = 0,1,2, \dots K$ (Residuals are not white noise (correlated))

Table 10. Residual White Noise Assumption Test

Lag	p-value	Decision
3	0,087	Accept H_0
10	0,157	Accept H_0
11	0,138	Accept H_0
12	0,064	Accept H_0

The acceptance of H_0 based on p-values exceeding 0,05 indicates that the residuals behave as white noise with no notable autocorrelation. As a result, the model is deemed effective in capturing key data structures, though additional validation may enhance overall reliability.

Multivariate Normal Residual Assumption

With a D value of 0.33 and a p-value of 0.09, the data satisfies the multivariate normality assumption, as the p-value is above the conventional significance level of 0.05.

Air Temperature Forecasting with the VARIMA Model

Table 11. Presents the results of air temperature forecasts for the next 19 months using the VARIMA model at the three BMKG stations in West Nusa Tenggara.

Month	Sultan Muhammad Kaharuddin	Zainuddin Abdul Madjid	Sultan Muhammad Salahuddin
December 2024	26,73	25,41	26,39
January 2025	27,80	27,38	28,31
February 2025	27,09	26,18	27,09
⋮	⋮	⋮	⋮
April 2026	27,38	26,55	27,51
May 2026	27,37	26,54	27,49
June 2026	27,47	26,64	27,59

Spatial Weight Matrix

Inverse Distance Weight Matrix

Table 12. shows the latitude and longitude coordinates for the three stations.

Station	Lattitude	Longitude
Sultan Muhammad Kaharuddin	-8,48845	117,41336
Zainuddin Abdul Madjid	-8,75277	116,24982
Sultan Muhammad Salahuddin	-8,54279	118,69280

Source: BMKG Website

Table 13. shows the Euclidean distances between the stations.

Station	Z_1	Z_2	Z_3
Z_1	0,000000	1,193185	1,280593
Z_2	1,193185	0,000000	2,451988
Z_3	1,280593	2,451988	0,000000

The resulting inverse distance weight matrix is:

$$\mathbf{W} = \begin{matrix} K \\ Z \\ S \end{matrix} \begin{bmatrix} 0 & 0,51766 & 0,48233 \\ 0,67266 & 0 & 0,32733 \\ 0,65691 & 0,34308 & 0 \end{bmatrix}$$

Normalized Cross-Correlation Weight Matrix

Symmetric matrix is calculated by components:

$$\mathbf{W} = \begin{matrix} K \\ Z \\ S \end{matrix} \begin{bmatrix} 0 & 0,44006 & 0,55993 \\ 0,42933 & 0 & 0,57066 \\ 0,48908 & 0,51091 & 0 \end{bmatrix}$$

Identification of GSTARIMA model

$$\begin{aligned} \nabla \mathbf{Z}(\mathbf{t}) = {} & \mathbf{\Phi_{10}Z(t-1)} + \mathbf{\Phi_{11}W^{(1)}Z(t-1)} + \mathbf{\Phi_{20}Z(t-2)} \\ & + \mathbf{\Phi_{21}W^{(1)}Z(t-2)} + \mathbf{\Phi_{30}Z(t-3)} \\ & + \mathbf{\Phi_{31}W^{(1)}Z(t-3)} - \mathbf{\Theta_{10}e(t-1)} \\ & - \mathbf{\Theta_{11}W^{(1)}e(t-1)} + \mathbf{e(t)} \end{aligned}$$

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Application of Inverse Distance Weighting

Table 14. Parameter Estimation of GSTARIMA Model $(3,1,1)_1$ with Inverse Distance Region Weight

Parameter	Estimasion	Stad. Error	p-value
Φ_{10}^{1}	-0,0959	0,2195	0,6626
Φ_{10}^{2}	0,5772	0,1937	0,0033
Φ_{10}^{3}	-0,4373	0,2533	0,0859
Φ_{11}^{1}	0,0228	0,2168	0,9165
Φ_{11}^{2}	-0,0250	0,2015	0,9012
Φ_{11}^{3}	0,0522	0,2731	0,8487
Φ_{20}^{1}	-0,2054	0,2069	0,3222
Φ_{20}^{2}	-0,4684	0,1986	0,0193
Φ_{20}^{3}	0,4308	0,2681	0,1097
Φ_{21}^{1}	0,1947	0,2238	0,3853
Φ_{21}^{2}	-0,2728	0,1845	0,1409
Φ_{21}^{3}	0,7162	0,2947	0,0160
Φ_{30}^{1}	-0,2727	0,2349	0,2470
Φ_{30}^{2}	-0,1326	0,1721	0,4418
Φ_{30}^{3}	-0,2218	0,3202	0,4893
Φ_{31}^{1}	-0,3712	0,2291	0,1068
Φ_{31}^{2}	0,0629	0,1714	0,7139
Φ_{31}^{3}	-0,8942	0,3213	0,0059
Θ_{10}^{1}	-0,0050	0,00054	$2,062 \times 10^{-16}$
Θ_{10}^{2}	-0,0045	0,00053	$9,167 \times 10^{-15}$
Θ_{10}^{3}	-0,0002	0,000024	$2,084 \times 10^{-16}$
Θ_{11}^{1}	0,0005	0,000036	$2,076 \times 10^{-32}$
Θ_{11}^{2}	0,0009	0,000055	$1,485 \times 10^{-35}$
Θ_{11}^{3}	0,0130	0,000629	$4,302 \times 10^{-46}$

The GSTARIMA $(3,1,1)_1$ model with inverse distance weighting is applied to the air temperature data at SMK

$$\begin{aligned}\nabla Z_1(t) = &-0,0959\nabla Z_1(t-1) + 0,0118\nabla Z_2(t-1)\\ &+ 0,0110\nabla Z_3(t-1) - 0,2054\nabla Z_1(t-2)\\ &+ 0,1007\nabla Z_2(t-2) + 0,0939\nabla Z_3(t-2)\\ &- 0,2727\nabla Z_1(t-3) - 0,1921\nabla Z_2(t-3)\\ &- 0,1790\nabla Z_3(t-3) + 0,0050e_1(t-1)\\ &- 0,0025e_2(t-1) - 0,0002e_3(t-1)\\ &+ e_1(t)\end{aligned}$$

The GSTARIMA $(3,1,1)_1$ model with inverse distance weighting is applied to the air temperature data at ZAM

$$\begin{aligned}\nabla Z_2(t) = &-0,0168\nabla Z_1(t-1) + 0,5772\nabla Z_2(t-1)\\ &- 0,0081\nabla Z_3(t-1) - 0,1835\nabla Z_1(t-2)\\ &- 0,4687\nabla Z_2(t-2) - 0,0892\nabla Z_3(t-2)\\ &+ 0,0423\nabla Z_1(t-3) - 0,1326\nabla Z_2(t-3)\\ &+ 0,0205\nabla Z_3(t-3) - 0,0006e_1(t-1)\\ &- 0,0045e_2(t-1) - 0,0002e_3(t-1)\\ &+ e_2(t)\end{aligned}$$

The GSTARIMA $(3,1,1)_1$ model with inverse distance weighting is applied to the air temperature data at SMS

$$\begin{aligned}\nabla Z_3(t) = &\ 0,0342\nabla Z_1(t-1) + 0,0179\nabla Z_2(t-1)\\ &- 0,4373\nabla Z_3(t-1) + 0,4704\nabla Z_1(t-2)\\ &+ 0,2457\nabla Z_2(t-2) + 0,4308\nabla Z_3(t-2)\\ &- 0,5874\nabla Z_1(t-3) - 0,3067\nabla Z_2(t-3)\\ &- 0,2218\nabla Z_3(t-3) - 0,0085e_1(t-1)\\ &- 0,0044e_2(t-1) + 0,0002e_3(t-1)\\ &+ e_3(t)\end{aligned}$$

Residual White Noise Assumption

Table 15. Residual White Noise Assumption Test

Lag	p-value	Decision
3	0,264	Accept H_0
4	0,398	Accept H_0
11	0,164	Accept H_0
12	0,111	Accept H_0

Since all p-values are above the common significance threshold (e.g., 0.05), the null hypothesis H_0 is accepted, confirming that the residuals exhibit white noise properties without significant autocorrelation. This suggests that the model sufficiently captures data patterns, eliminating the need for further adjustments related to residual autocorrelation.

Multivariate Normal Residual Assumption

With a D value of 0.54 and a p-value of 0.93, the data satisfies the multivariate normality assumption, as the p-value is above the conventional significance level of 0.05.

GSTARIMA Forecasting $(3,1,1)_1$ Distance Inverse Weighting

Table 16. Forecast of air temperature for the next 19 months at the three BMKG stations in West Nusa Tenggara

Month	SMK	ZAM	SMH
December 2024	27,57	26,28	27,27
January 2025	27,24	26,97	27,09
February 2025	27,11	26,72	27,56
⋮	⋮	⋮	⋮
May 2026	28,46	27,62	29,63
June 2026	28,52	27,76	28,93

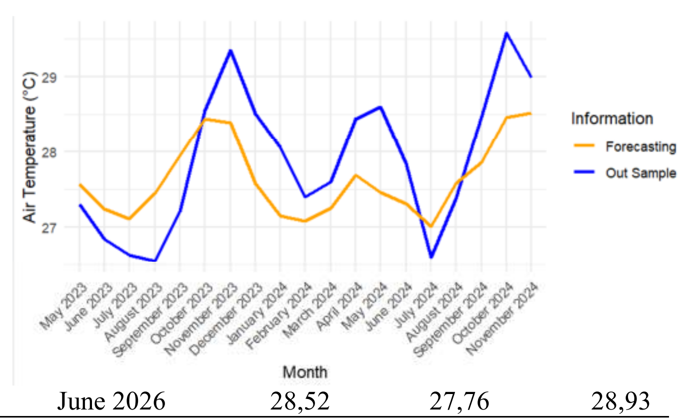

Figure 5. Out-of-Sample Data and Air Temperature Forecast Plot at Sultan Muhammad Kaharuddin Station with Inverse Distance Weighting

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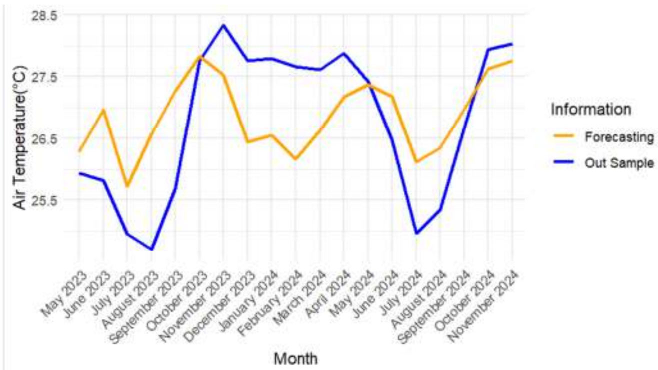

Figure 6. Out-of-Sample Data and Air Temperature Forecast Plot at Zainuddin Abdul Madjid Station with Inverse Distance Weighting

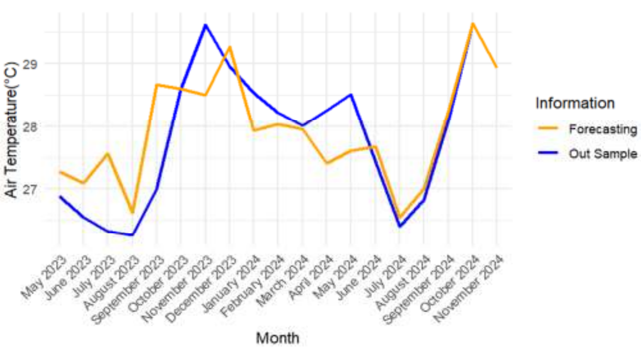

Figure 7. Out-of-Sample Data and Air Temperature Forecast Plot at Sultan Muhammad Salahuddin Station with Inverse Distance Weighting

Application of Cross-Correlation Normalization Weights

Table 17. Estimation of the GSTARIMA $(3,1,1)_1$ Model Parameters with Cross-Correlation Normalization Weighting

Parameter	Estimasion	Stad. Error	p-value
Φ_{10}^1	-0,0464	0,2218	0,8346
Φ_{10}^2	0,5779	0,1993	0,0042
Φ_{10}^3	-0,5286	0,2717	0,0532
Φ_{11}^1	0,0263	0,2196	0,9047
Φ_{11}^2	-0,0367	0,2090	0,8608
Φ_{11}^3	0,0982	0,3090	0,7511
Φ_{20}^1	-0,2343	0,2104	0,2668
Φ_{20}^2	-0,5017	0,2027	0,0142
Φ_{20}^3	0,5459	0,2918	0,0629
Φ_{21}^1	0,1390	0,2225	0,5327
Φ_{21}^2	-0,2596	0,1870	0,1667
Φ_{21}^3	0,8399	0,3158	0,0085
Φ_{30}^1	-0,2673	0,2318	0,2502
Φ_{30}^2	-0,1133	0,1766	0,5220
Φ_{30}^3	-0,2850	0,3621	0,4322
Φ_{31}^1	-0,3256	0,2275	0,1539
Φ_{31}^2	0,1156	0,1763	0,5129
Φ_{31}^3	-1,0669	0,3516	0,0027
Θ_{10}^1	-0,0062	0,00067	$2{,}093 \times 10^{-16}$
Θ_{10}^2	-0,0084	0,00097	$1{,}036 \times 10^{-14}$
Θ_{10}^3	-0,00049	0,000053	$1{,}963 \times 10^{-16}$
Θ_{11}^1	0,00159	0,00010	$1{,}916 \times 10^{-32}$
Θ_{11}^2	0,0013	0,000081	$1{,}974 \times 10^{-35}$
Θ_{11}^3	0,0138	0,000664	$5{,}405 \times 10^{-46}$

Residual White Noise Assumption Cross Correlation Weighting

$H_0 : \rho_1 = \rho_2 = \cdots = \rho_K = 0$ (The residuals exhibit white noise characteristics (uncorrelated))

H_1 : There is at least one $\rho_j \neq 0, j = 0,1,2, \dots K$ (The residuals do not exhibit white noise characteristics (correlated))

Table 18. Residual white noise assumption test with cross-correlation weighting

Lag	p-value	Decision
3	0,259	Accept H_0
4	0,392	Accept H_0
11	0,164	Accept H_0
12	0,110	Accept H_0

The test results show that all p-values exceed the common significance level (e.g., 0.05), leading to the acceptance of H_0. This indicates that the residuals exhibit white noise characteristics, with no significant autocorrelation. The implication is that the model effectively captures the data patterns, and no major information is left in the residuals. Therefore, no further adjustments are needed to address autocorrelation.

Multivariate Normal Residual Assumption

With a D value of 0.56 and a p-value of 0.939, the data satisfies the multivariate normality assumption, as the p-value is above the conventional significance level of 0.05.

Table 19. Air temperature forecast for the next 19 months at three BMKG stations in West Nusa Tenggara**.**

Month	SMK	ZAM	SMH
December 2024	27,57	26,28	27,27
January 2025	27,24	26,97	27,09
February 2025	27,11	26,72	27,56
⋮	⋮	⋮	⋮
April 2026	27,86	26,98	28,25
May 2026	28,46	27,62	29,63
June 2026	28,52	27,76	28,93

Root Mean Square Error (RMSE) Value

The results of the RMSE calculation for both the weighting matrices and the VARIMA and GSTARIMA model used can be seen in Table 23.

Table 20. RMSE Values for Each Model

Models	Station	Average

	SMK	ZAM	SMH	RMSE
VARIMA (3,1,1)	0,961	0,946	0,959	2,868
GSTARIMA (3,1,1)$_1$ Inverse Distance	1,098	1,016	0,706	**2,821**
GSTARIMA (3,1,1)$_1$ Cross Correlation	1,100	1,017	0,705	2,822

B. Use of Simulation software

The entire process of data analysis, modeling, and forecasting in this research was performed using the **R programming language**, which provides extensive capabilities for time series analysis, statistical modeling, and spatial data processing. The following R packages and tools were employed:

- tseries: for conducting the Augmented Dickey-Fuller (ADF) test to assess stationarity.
- forecast: for time series transformations, including Box-Cox transformation and differencing.
- vars: for constructing and estimating the VARIMA model, including order selection using AIC.
- spdep: for computing Moran's I statistic to assess spatial autocorrelation.
- Custom-built R functions: for calculating distance inversion weights and cross-correlation normalization required in the GSTARIMA model.
- ggplot2: for data visualization, including time series plots, residual diagnostics, and spatial maps.
- Base R functions: for descriptive statistics, transformation, and data handling.

The choice of R was motivated by its robust support for statistical modeling, its open-source nature, and its strong community support, which ensures reproducibility and transparency in scientific computation. Additionally, R allowed for flexible customization needed to implement the GSTARIMA model, which is not available in standard statistical software.

Through the integration of various statistical and spatial tools in R, this research successfully demonstrated a comparative analysis of two powerful forecasting models, offering insights into their performance in the context of climate data.

III. GET PEER REVIEWED

Before finalizing this manuscript for publication, the authors conducted an internal peer review process to ensure the quality and eligibility of the research paper for scholarly publication. This manuscript has been critically reviewed by:

1. **First Supervisor – Prof. Dr. Dr. Georgina Maria Tinungki, M.Si**
   - Provided input on the structure of the manuscript and the clarity of the discussion on the GSTARIMA and VARIMA models.
   - Recommended the addition of more detailed explanations regarding the selection of spatial weights using normalized cross-correlation and inverse distance matrix.
2. **Second Supervisor – Prof. Dr. Nurtiti Sunusi, M.Si**
   - Emphasized the importance of diagnostic checking in time series modeling and suggested a more thorough explanation of the ACF/PACF results.
   - Corrected several technical terms and advised improvements to the referencing format.
3. **Peer Reviewer (Postgraduate Statistics Student)**
   - Provided suggestions related to the interpretation of forecasting results and recommended the use of more informative data visualizations.

Follow-Up Actions

Based on the above feedback, the authors made several improvements to the manuscript, including:

- Enhancing the **Methodology** section, particularly the explanation of how spatial weight matrices were constructed.
- Refining the **Results and Diagnostic** sections with clearer interpretation and elaboration.
- Updating **visual presentations**, especially the comparison plots between actual and forecasted data.

This peer review process has been instrumental in improving the overall quality of the manuscript in both content and presentation.

IV. IMPROVEMENT AS PER REVIEWER COMMENTS

Based on the comments and feedback received during the review and supervision process, several revisions have been made to this manuscript, as follows:

1. Explanation of Spatial Weight Matrices Reviewers recommended a more detailed explanation of the construction of spatial weight matrices. In response, the manuscript now includes a more comprehensive description of the inverse distance matrix and the normalized cross-correlation matrix, including their formulas, weighting procedures, and examples of their application in the GSTARIMA model. This addition aims to clarify the theoretical justification behind the use of both spatial approaches.
2. Parameter Estimation of the Models Several reviewers requested a more thorough explanation of the parameter estimation process in the VARIMA(3,1,1) and GSTARIMA(3,1,1) models. In response, the manuscript has been enriched with tables of estimated parameters, which include:

- The values of autoregressive (AR) and moving average (MA) coefficients,
- Spatial parameters for each observed location,
- The statistical significance (p-values) of each parameter,
- Model performance indicators such as AIC and RMSE.

Estimation was conducted using the least squares method for the VARIMA model and iterative generalized least squares for the GSTARIMA model, taking into account both spatial and temporal dimensions simultaneously.

3. Model Diagnostic Analysis
   Reviewers suggested additional diagnostic testing to validate model adequacy. In response, the manuscript now includes:
   - Plots of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the residuals,
   - Ljung-Box test to detect the presence of autocorrelation in the residuals,
   - Normality test using the Jarque-Bera test.

The results show that the residuals from both models exhibit no significant autocorrelation and are normally distributed, indicating the models are statistically valid for forecasting.

4. Forecasting Result Comparison
   Reviewers requested a more detailed discussion of the forecasting results for both models. The manuscript has been revised to include:
   - Graphs of 7-day ahead forecasts for each model,
   - A comparative analysis using RMSE values to assess accuracy.

The results indicate that the GSTARIMA model generally outperforms the VARIMA model in terms of forecasting accuracy, especially in locations with strong spatial interdependence.

5. Language and Structural Improvements
   Supervisors and reviewers also suggested improving the academic tone and structure of the manuscript. As a response, grammatical corrections were made, terminology was refined, and sentence structures were revised to make the text more concise, systematic, and aligned with academic writing standards.

After submission SHIYOU will send you reviewer comment within 10-15 days of submission and you can send us the updated paper within a week for publishing.

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V. CONCLUSION

The best model for forecasting average air temperature in West Nusa Tenggara is GSTARIMA $(3,1,1)_1$ with inverse distance weighting, which achieved the lowest RMSE of 2.821, meeting model feasibility criteria. This model was estimated using the Ordinary Least Squares (OLS) method. Forecasts from December 2024 to June 2025 closely align with out-of-sample data, demonstrating accurate predictions. The GSTARIMA $(3,1,1)_1$ model, which incorporates temporal and spatial dependencies, provides robust temperature predictions, making it valuable for climate analysis and forecasting. These findings are important for improving early warning systems, supporting agricultural planning, and enhancing disaster preparedness in the West Nusa Tenggara region. By providing reliable temperature forecasts, the model can help policymakers, farmers, and local communities make informed decisions to mitigate the impacts of extreme weather conditions.

By incorporating both spatial and temporal dependencies, the model enhances prediction accuracy, surpassing traditional approaches. This improved forecasting capability supports climate monitoring, disaster preparedness, and agricultural planning, enabling better decision-making for extreme weather events. Additionally, the study advances spatial-temporal modelling techniques, which can be applied to other meteorological variables, further improving climate forecasting methods. Overall, these findings provide valuable insights for policymakers, researchers, and industries reliant on accurate temperature predictions.

APPENDIX

Appendix. VARIMA Results

Number of Observations	75
Number of Pairwise Missing	0
Observation(s) eliminated by differencing	1

Type of Model	VARMA(3,1)
Estimation Method	Maximum Likelihood Estimation

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The author is also grateful to all colleagues and friends who have offered encouragement and assistance during the preparation of this paper.

Finally, the author hopes that this research will contribute positively to the development of knowledge and science, particularly in the fields of statistics and environmental modeling.

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