

# Handling Space-Time Autocorrelation Using Eigenvector Filtering-Varying Coefficient Model in Rainfall Modeling Based on CMIP6 Output and Local Characteristic Information

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## Abstract

In the modern era, the possibility for large-scale data collection becomes better and easier through various methodologies. When data are collected with respect to both spatial and temporal dimensions, it is referred to as spatiotemporal data. Such datasets often exhibit autocorrelation arising from spatial proximity, temporal continuity, or the interaction of both dimensions, which is commonly called space-time autocorrelation. Rainfall measurements recorded at different locations and at different times are important due to their relevance in various fields. Due to its spatiotemporal nature, rainfall data often exhibit space-time autocorrelation. Empirical studies further show that rainfall patterns exhibit spatial and temporal variations, which contribute to heterogeneity across regions and times. Motivated by these challenges, this study aims to develop a modeling framework that integrates Eigenvector Space-Time Filtering (ESTF) based on the Varying Coefficient Model to address complex space-time autocorrelations in rainfall data, while integrating CMIP6 global climate projections with local characteristics to enhance the model's relevance to regional conditions. This study uses General Circulation Model (GCM) output from CMIP6-DCPP and incorporates local geographical and environmental features in the modeling process. The GCM output data is represented by 22 principal components to overcome multicollinearity. Furthermore, the varying coefficient components are used to explore the effect of spatial and temporal varying variables on rainfall. The modeling results show that the use of space-time dependency structure in the eigenvector filtering approach effectively reduces space-time autocorrelation. In addition, the performance of the model also improved compared to the OLS, ESF, and ESF-VC models. The final ESTF-VC model shows the best performance based on the RMSE (58.33),  $R^2$  (0.64), and AIC (22128.94) values. Based on these results, it can be concluded that the ESTF-VC model is able to handle space-time autocorrelation in rainfall modeling using GCM outputs and local characteristic information and improve estimation performance.

**Keywords:** eigenvector space-time filtering, rainfall, spatiotemporal data, varying coefficient model

## 1. INTRODUCTION

The collection of large-scale data associated with specific spatial and temporal coordinates can be done through various methods. Data that includes both spatial and temporal attributes are commonly referred to as spatiotemporal data [1]. This type of data often exhibits autocorrelation, which signifies statistical dependence among observations across space and time. Such dependence can arise from spatial proximity, temporal proximity, or a combination of both, collectively referred to as space-time autocorrelation. This phenomenon is in

line with Tobler's First Law of Geography, which states that "everything is related to everything else, but things that are near are more related than things that are far away." Traditional linear modeling techniques, such as regression, which assume independence among observations, can be invalid under these conditions. To overcome this, one effective strategy is the Eigenvector Space-Time Filtering (ESTF) method. This approach involves creating a modified space-time adjacency matrix and decomposing it into a set of orthogonal eigenvectors [2], which serve as spatial and temporal filters within the eigenvector filtering framework [3]. Over time, the eigenvector filtering technique has been extended and applied in various modeling contexts, including its integration in the Varying Coefficient (VC) model framework [4]. This extension allows modeling spatial data with location-specific effects, a characteristic known as spatial non-stationarity.

Rainfall is a pivotal source of information in various disciplines and applications. When rainfall data are collected with reference to spatial and temporal dimensions, they often exhibit space-time

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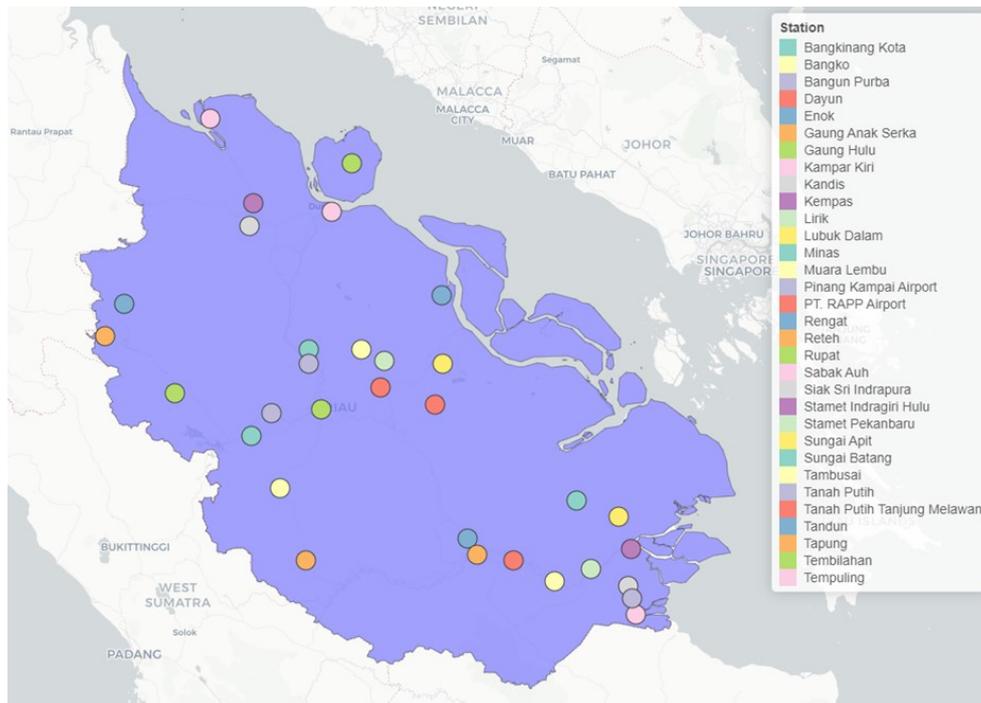
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**Figure 1.** Location of Riau Rainfall Observation Stations.

**Table 1.** Research data and data sources.

Research Data	Data Source
Rainfall observation data	Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG)
CMIP6-DCPP with CNRM-ESM2	<a href="https://esgf.llnl.gov/nodes.html">https://esgf.llnl.gov/nodes.html</a>
El Nino-Southern Oscillation (ENSO)	<a href="https://www.daculaweather.com/">https://www.daculaweather.com/</a>
Altitude of rain station location	<a href="https://earth.google.com/web/">https://earth.google.com/web/</a>
Normalized Difference Vegetation Index	<a href="https://code.earthengine.google.com/">https://code.earthengine.google.com/</a>
Station location based on the equator	<a href="https://earth.google.com/web/">https://earth.google.com/web/</a>

autocorrelation. In addition, previous studies have shown that rainfall patterns in a region are affected by spatial and temporal variability [5][6]. Estimating rainfall is inherently complex due to the many interacting factors. One effective method to overcome this complexity is to use Statistical Downscaling (SD) techniques. This method utilizes the output of General Circulation Models (GCMs) to estimate point-scale rainfall by establishing functional relationships between large-scale atmospheric predictors and local-scale rainfall responses [7]. In this study, the GCM outputs used are from the Coupled Model Intercomparison Project Phase 6 (CMIP6), specifically using data from the Decadal Climate Prediction Project (DCPP).

However, SD approaches that rely solely on GCM outputs tend to insufficiently capture local

effects on rainfall estimates due to the inherently coarse spatial resolution of GCMs [8]. To overcome this limitation, this study incorporates additional information on local characteristics into the modeling framework. The selected study area is Riau Province, Indonesia, an area known for its high vulnerability to forest and land fires. Riau has approximately 5.09 million hectares of peatland, which represents 56.42% of the total peatland area in Sumatera [9]. The primary objective of this research is to develop a modeling framework that utilizes ESTF based on the VC model to address complex space-time autocorrelation in rainfall data. Additionally, this research integrates statistical methods into the field of climate science by combining global climate projections from CMIP6 with specific local characteristics, resulting in a model that better aligns with regional conditions.

## 2. MATERIALS AND METHODS

### 2.1. Data

This study uses several types of data consisting of local, global, and additional environmental variables. Local data consists of rainfall observations at 32 meteorological stations spread across Riau Province (Figure 1). The global data used comes from the output of the GCM, specifically from the CMIP6-DCPP dataset using the CNRM-ESM2 model. This study also involved several local characteristic information variables, including altitude, vegetation, and distance from the equator. The elevation of a location is known to have a significant effect on rainfall patterns in a location [10], and previous studies have also indicated that vegetation conditions are correlated with rainfall variability [11]. Riau Province is classified as an equatorial rainfall zone, characterized by bimodal rainfall peaks, due to its geographical position along the equator [12]. Therefore, this study will include the variable distance of each rainfall station from the equator. In addition to local and global inputs, another important dataset included is the El Niño-Southern Oscillation (ENSO) index, which captures sea surface temperature anomalies in the Pacific Ocean [13]. The ENSO variable was chosen because El Niño conditions can cause a significant decrease in rainfall during the dry season in Indonesia [14]. All information regarding the data and data sources for the study is described in Table 1.

### 2.2. Modeling Procedure

The modeling procedure in this study is

generally described in Figure 2. The Eigenvector Spatial Filtering-based Varying Coefficient (ESF-VC) model, originally introduced by Griffith in 2008 [4], was formulated as an extension of the Geographically Weighted Regression framework. The basic idea behind the ESF-VC model is to include the interaction between each explanatory variable and a set of spatial eigenvectors. This model was further developed by integrating a random effect component. This component ensures that all selected eigenvectors can be incorporated into the model with contributions controlled through variance distribution, resulting in a more flexible approach with equations described as follows Eq. 1 [15].

$$Y = b_1 \mathbf{1} + E\gamma_1 + \sum_{p=2}^P X_p \circ \beta_p + \varepsilon \quad \varepsilon \sim N(\mathbf{0}, \sigma^2 I) \quad (1)$$

where  $Y$  is an  $n \times 1$  response variable vector, and  $X_p$  is the  $p$ -th covariate vector of size  $n \times 1$ . Parameter  $b_p$  in Equation (1) is defined as:

$$\beta_p = b_p \mathbf{1} + E\gamma_p \quad \text{with} \quad \gamma_p \sim N(\mathbf{0}_K, \sigma_{p(\gamma)}^2 \Lambda(\alpha_p))$$

where  $b_p$  is the constant coefficient of each predictor. Meanwhile, the parameter  $b_p$  is a varying coefficient calculated based on the values of  $b_p \mathbf{1}$  and  $E\mathbf{g}_p$ . Matrix  $E$  represents a matrix comprising  $K$  eigenvectors corresponding to positive eigenvalues. The term  $s_{p(g)}^2$  is the variance parameter, while  $L(\alpha_p)$  is  $K \times K$  diagonal matrix whose  $k$ -th diagonal entry is defined as  $\lambda_k(\alpha_p) = \left( \sum_k \lambda_k / \sum_k \lambda_k^{\alpha_p} \right) \lambda_k^{\alpha_p}$  [16]. The vector  $\mathbf{g}_p$  corresponds to a random coefficient associated with the spatial variation parameter  $s_{p(g)}^2$  and the spatial scale parameter  $\alpha_p$ . The parameter  $s_{p(g)}^2$  governs the

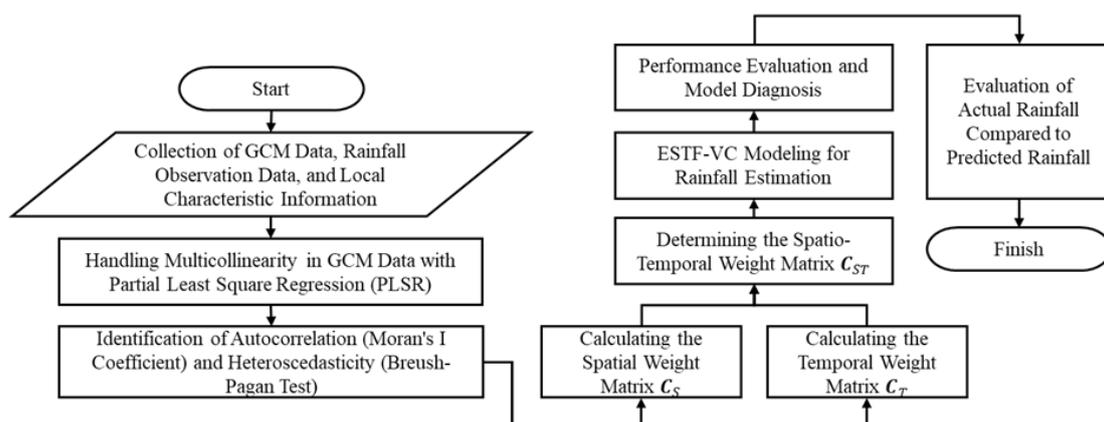
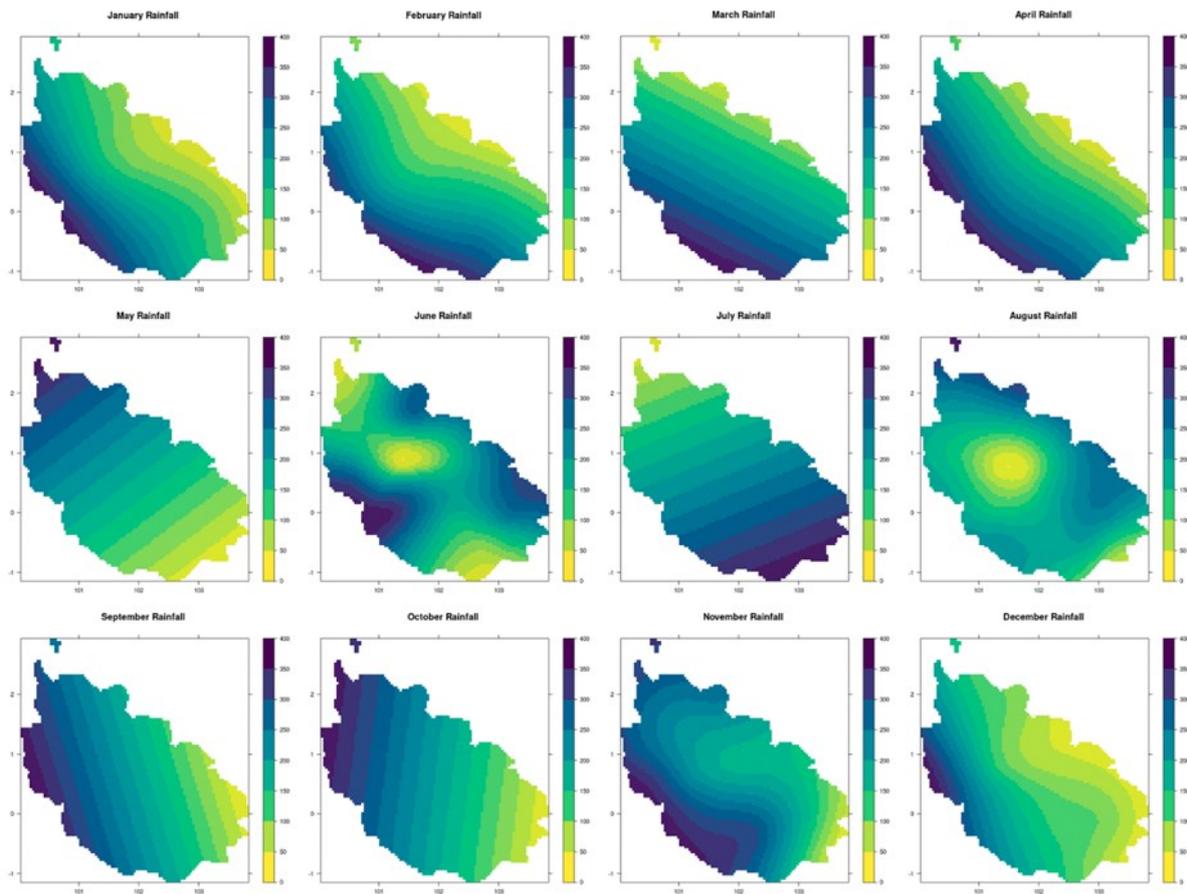


Figure 2. Flowchart of modeling procedure.



**Figure 3.** Characteristics of average rainfall by month.

degree of spatial variation, while  $a_p$  regulates the effective spatial range or scale. The ESF-VC model, as expressed in Equation (1), conforms to the general structure of a linear mixed-effects model, and the parameters are typically estimated using either Maximum Likelihood (ML) or Restricted ML (ReML) approaches.

The ESTF approach has been shown to effectively handle spatial and temporal autocorrelation in spatiotemporal data. In addition, the ESTF method is able to capture almost the entire spatial structure present in the data by utilizing random components in the model [2]. The development of the ESTF-VC model is done by performing an eigenvectors decomposition of the  $MC_{ST}M$  matrix on the Moran's I coefficient equation for space-time autocorrelation with the following Equation 2.

$$Mcoef_{ST} = \frac{nT}{\mathbf{1}'C_{ST}\mathbf{1}} \frac{Y' MC_{ST}MY}{Y'MY} \quad (2)$$

where matrix  $M$  is defined as the centering projection matrix  $(I - 1(1\phi)^{-1}1\phi)$  with size  $nT \times nT$ .

The notation  $n$  indicates the number of locations, and  $T$  is the number of time periods. This matrix centers the data to a mean of zero and ensure that spatial autocorrelation is calculated against deviations from the mean. The  $C_{ST}$  matrix is a spatiotemporal weight matrix, which in this study uses a contemporaneous space-time dependency structure with the following Equation 3.

$$C_{ST} = I_T \otimes C_S + C_T \otimes I_S \quad (3)$$

The  $C_S$  and  $C_T$  are the spatial and temporal weight matrices defined as follows Eq. 4.

$$C_S = \exp\left(\frac{-d(i,j)}{r}\right) \quad C_T = \frac{1}{|u-t|} \quad (4)$$

The contemporaneous space-time dependency structure represents the relationship between values at a particular location and time and values at the same location at an earlier time, as well as values at surrounding locations at the same time. The result of the eigenvector decomposition of the  $MC_{ST}M$  matrix is denoted by  $E_{full}$  and several eigenvectors

will be selected based on positive eigenvalues and collected in the  $E$  matrix. These selected eigenvectors will be used in the ESTF-VC model based on Equation (1). Hereafter, this model will be referred to as the ESTF-VC model.

### 3. RESULTS AND DISCUSSIONS

The rainfall dataset used in this study consists of monthly rainfall records covering the period 2015 to 2019, obtained from 32 rainfall observation stations. The spatial characteristics of average monthly rainfall across the region are illustrated in Figure 3, while the temporal rainfall pattern at each station is presented in Figure 4. Figure 3 depicts the spatial distribution of average rainfall across Riau Province over a five-year period, with darker map

colors indicating higher rainfall intensity. Meanwhile, Figure 4 highlights that most stations show a bimodal rainfall pattern, characterized by two peaks of rainfall each year. This pattern is consistent with the equatorial rainfall pattern prevalent in Riau Province, which is traversed by the equator and generally characterized by a peak rainy season occurring around March and October [12]. The GCM output data used in this study are sourced from the CMIP6-DCPP CNRM-ESM2 model with a spatial domain consisting of a 6×6 grid configuration, resulting in a total of 36 grid points. The high level of correlation between the grids can be seen from the Variance Inflation Factor (VIF) value in Figure 5 and the correlation coefficient (Figure 6). The strong correlation indicates the presence of multicollinearity in the

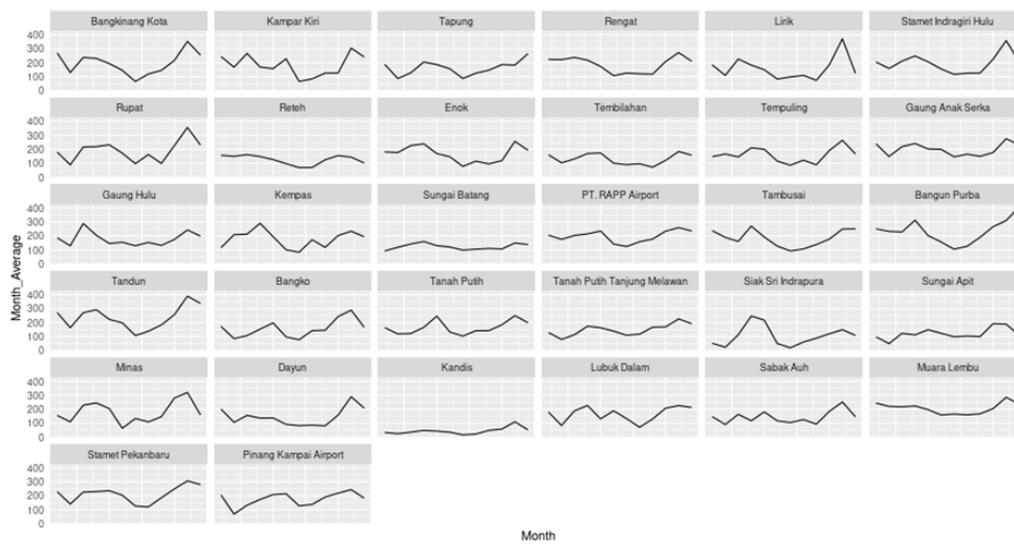


Figure 4. Characteristics of average rainfall of each station.

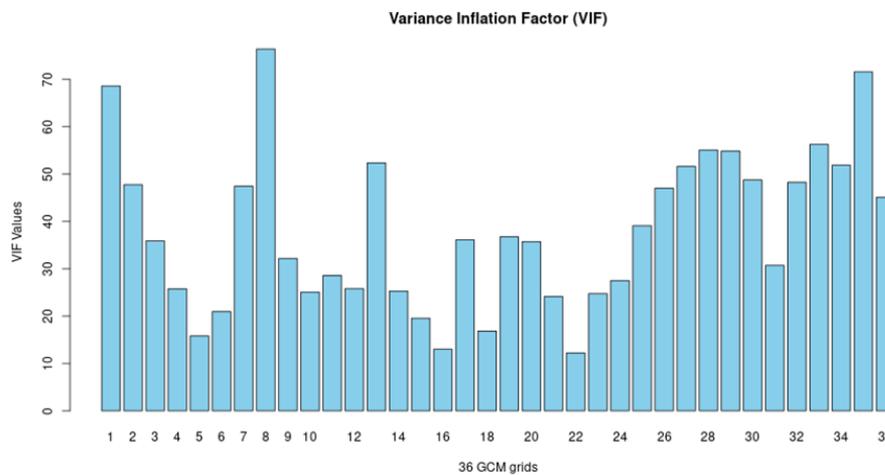


Figure 5. VIF value of 36 GCM grids.

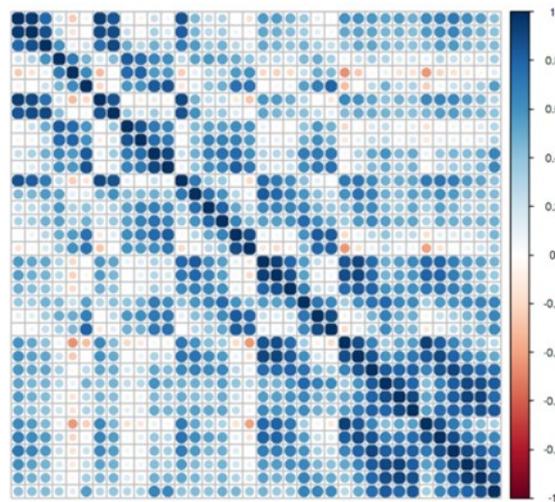


Figure 6. Correlation coefficient.

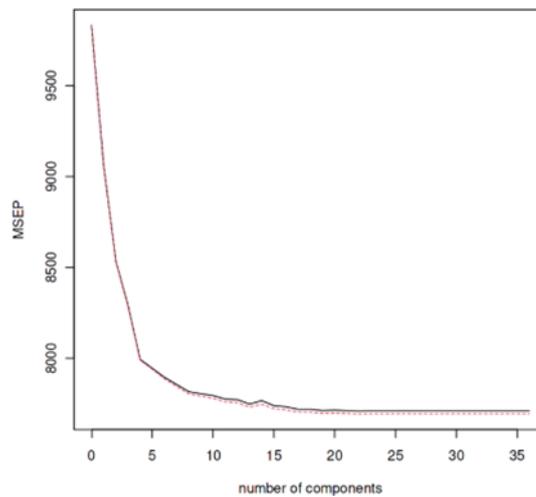


Figure 7. Optimum component.

Table 2. Identification of autocorrelation and heteroskedasticity.

Identification	Statistic Test	<i>p-value</i>
Autocorrelation	Moran's I Coefficient: 0.1409	0.0000
Heteroscedasticity	Breusch-Pagan Stat: 73.0225	0.0000

data set. To address this issue, this study applies the Partial Least Squares Regression (PLSR) technique, which reduces multicollinearity by transforming the original grid variables into a reduced set of orthogonal components. Specifically, the GCM data were reduced to 22 principal components, as illustrated in Figure 7.

The identification of space-time autocorrelation was carried out using monthly rainfall observation data collected over a five-year period from 32 observation stations. This identification was based on the calculation of Moran's I index, which has been adapted to account for space-time dependence.

In addition, an assessment of the heteroscedasticity assumption was conducted using the Breusch-Pagan test, which was applied to a regression model fitted with predictor variables derived from data that had been adjusted for multicollinearity using the PLSR method. Rainfall observation data in Riau Province showed significant space-time autocorrelation, as shown in Table 2, with a Moran's I value of 0.1409 and a *p-value* of 0.0000. Using a significance level of 5% ( $\alpha = 0.05$ ), and under the null hypothesis ( $H_0$ ) which assumes that the observed data are randomly distributed, the null hypothesis is rejected. This result confirms the presence of space-time

autocorrelation in the rainfall data. In terms of heteroscedasticity, the Breusch-Pagan test also leads to the rejection of the null hypothesis at the 5% significance level, where  $H_0$  states that the error variance is constant. Therefore, it can be concluded

that there is heteroscedasticity in the regression model. Based on both diagnostic evaluations, the ESTF-VC model is considered a suitable approach for modeling rainfall patterns in Riau Province.

Based on the analysis results, the eigenvector

**Table 3.** Estimated parameters and statistical significance of local characteristic variables.

Coefficient	Coefficient Estimates			Proportion of Significant Coefficients		Effect Description *
	Min	Mean	Max	Sig (p < 0.1)	%	
Enso	-31.552	-2.852	48.654	233/1920	12%	-
Altitude	-1.694	0.111	1.057	133/1920	7%	-
Vegetation	-58.857	-14.665	20.858	74/1920	4%	-
Equator	-0.899	-0.462	-0.074	975/1920	51%	Local

\*) The threshold criterion for local effect in this study is that at least 50% of the overall variable coefficients have a significant effect on rainfall estimation.

**Table 4.** Further analysis of ENSO, altitude, and vegetation variables.

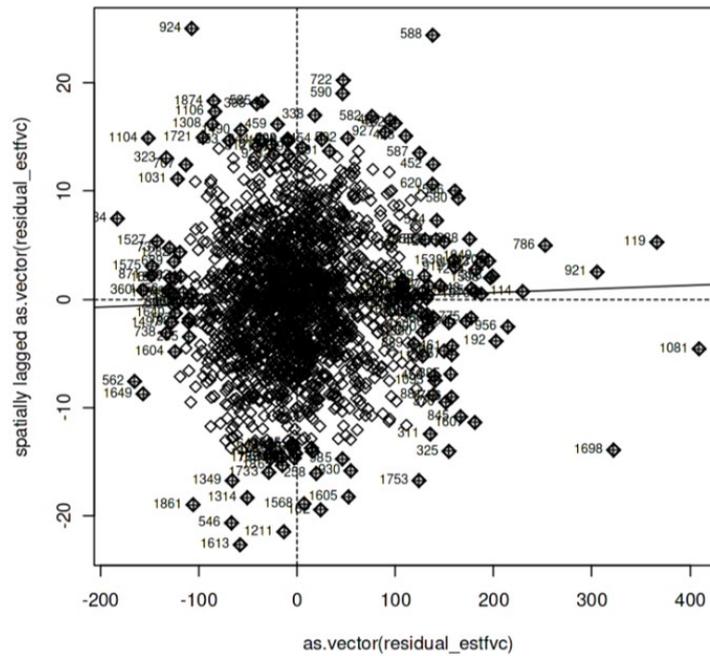
Coefficient	Constant Coefficient Estimates	p-value
ENSO	-5.159	0.097
Altitude	0.224	0.302
Vegetation	-10.532	0.294

**Table 5.** Proportion of significant coefficients on principal component variables.

Component	Sig (p < 0.01)	%	Component	Sig (p < 0.01)	%
Comp1	1542 / 1920	80%	Comp12	1070 / 1920	56%
Comp2	1481 / 1920	77%	Comp13	111 / 1920	6%
Comp3	1700 / 1920	89%	Comp14	1690 / 1920	88%
Comp4	652 / 1920	34%	Comp15	1920 / 1920	100%
Comp5	490 / 1920	26%	Comp16	890 / 1920	46%
Comp6	1800 / 1920	94%	Comp17	182 / 1920	9%
Comp7	1842 / 1920	96%	Comp18	10 / 1920	1%
Comp8	623 / 1920	32%	Comp19	1200 / 1920	63%
Comp9	248 / 1920	13%	Comp20	340 / 1920	18%
Comp10	104 / 1920	5%	Comp21	0 / 1920	0%
Comp11	0 / 1920	0%	Comp22	123 / 1920	6%

**Table 6.** Comparison of modeling results.

Model	Modelling Result			Residual Analysis	
	RMSE	R <sup>2</sup>	AIC	Moran's I	P-Value
OLS	85.48	0.25	22558.72	0.1409	0.0000
ESF	84.31	0.27	30039.73	0.1251	0.0000
ESF-VC	76.32	0.40	22199.90	0.0255	0.0000
ESTF	76.42	0.40	22232.82	0.0300	0.0000
ESTF-VC	58.33	0.64	22128.94	0.0033	0.3899



**Figure 8.** Residual Moran's Scatterplot.

decomposition of the  $MC_{STM}$  matrix in this study produced 1920 eigenvectors collected in  $E_{full}$  matrix. Next, several eigenvectors from the  $E_{full}$  matrix will be selected based on positive eigenvalues, resulting in 476 eigenvectors. These eigenvectors are collected in a matrix  $E$  with dimensions  $1920 \times 476$ .

The set of selected eigenvectors formed the  $1920 \times 476$  matrix  $E$  and was used in ESTF-VC modeling as formulated in Equation (1). Modeling results for local characteristic variables are presented in Table 3, while results for 22 principal components derived from GCM data are shown in Table 4. Based on these results, of all the local characteristic variables, only the Equator variable shows a significant local effect on rainfall patterns in Riau Province. Meanwhile, ENSO, Altitude, and Vegetation (NDVI) variables do not show significant local effects. In addition, the results of the analysis of 22 principal component variables obtained from the CMIP6-DCPP output are summarized in Table 5. Applying the threshold criterion where principal component variables are considered to exhibit local effects if at least 50% of their coefficients are statistically significant, the results in Table 5 show that 9 out of 22 principal component variables meet this condition. In addition, the analysis shows that 2 principal components show no local effects at all, as none of

the coefficients are statistically significant. These findings suggest that the dimensionality reduction process applied to the CMIP6-DCPP data-through principal component analysis-not only helps to reduce multicollinearity, but also affects the ability to capture spatially varying relationships in rainfall dynamics in Riau Province.

Further analysis was conducted to determine how ENSO, altitude, and vegetation variables affect rainfall. This analysis was conducted by including all three variables in the ESTF-VC model but with constant (non-varying) coefficient settings. As presented in Table 4, the results show that none of the variables have a statistically significant global effect on rainfall in Riau Province using significance level  $\alpha = 1\%$ . Based on the results of further analysis, the final model used in rainfall estimation is the ESTF-VC model, which involves 22 principal components of GCM outputs and local characteristic variables of location distance from the equator. To evaluate the performance of the proposed model, the ESTF-VC model is compared with several alternative models, namely OLS, ESF, ESF-VC, and ESTF, based on performance measures such as RMSE, AIC, and  $R^2$ , with the comparison results summarized in Table 6. The OLS model represents the conventional multiple linear regression approach. The ESF model incorporates spatial filtering but does not account

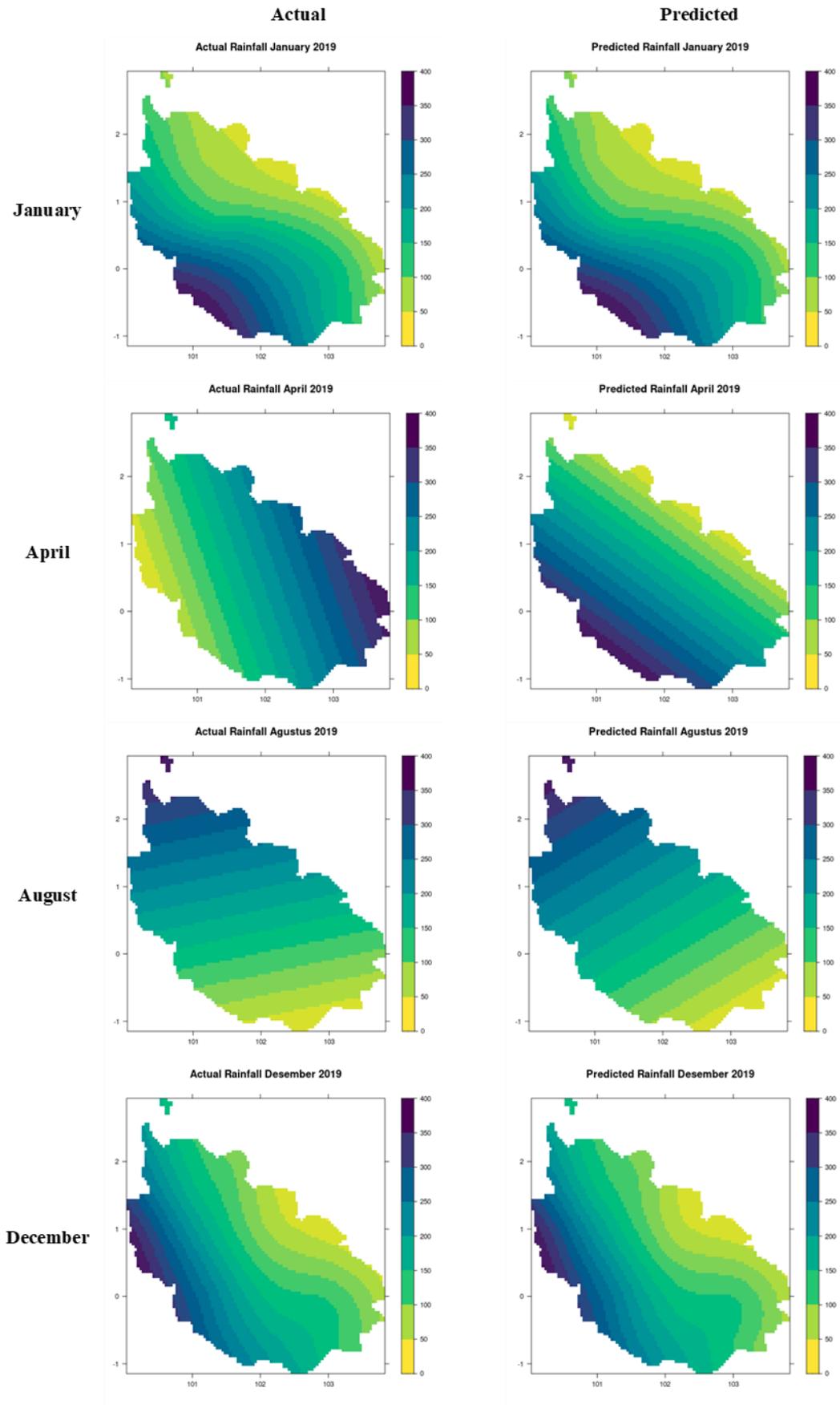


Figure 9. Actual and predicted rainfall for january, april, august, and december 2019.

for space-time dependence or varying coefficients. The ESF-VC model accommodates spatial variation in the coefficients but lacks the structure of space-time dependence. The ESTF model incorporates space-time filtering but does not allow for coefficient variation. Based on the modeling results, the ESTF-VC model produces the smallest RMSE and AIC values, which are 61.71 and 22167.22, respectively. Furthermore, error diagnostics using the Moran's I test at a 5% significance level, under  $H_0$  of spatial randomness in the residuals, shows that the ESTF-VC model successfully eliminates spatial autocorrelation in the residuals, as evidenced by a p-value greater than 0.05. This finding is also reinforced by the residual Moran's scatterplot (Figure 8). The results in this study confirm that filtering utilizing a spatiotemporal structure weight matrix is capable of handling space-time autocorrelation [2].

The final stage of this analysis is to create a comparison map between observed rainfall data and rainfall predictions generated by the modeling process. This comparison is done by selecting representative time points within the entire modeling period. Specifically, the selected months are January, April, August, and December 2019. The results of this comparison are presented in Figure 9. In January, August, and December 2019, the pattern similarity between actual and predicted rainfall is very high. This indicates that in these months, the ESTF-VC model is able to predict rainfall well. Whereas in April 2019, the actual and predicted rainfall show quite striking differences, with patterns that tend to be different or even opposite. This difference may be caused by the migration of the Intertropical Convergence Zone to the north in April, which directly changes the distribution of rainfall [17].

Some findings on the comparison of actual and predicted rainfall show that while the model can accurately capture rainfall patterns for certain periods, there are still inconsistencies in other periods. This highlights the need for further investigation to improve the model's performance across different time contexts. Rainfall modeling in this study utilizes GCM output data and local characteristic information. Therefore, the accuracy of the prediction results is strongly affected by several factors, such as the accuracy of the selection

of GCM output data and the historical quality of the GCM itself [18][19]. In addition to GCM output data, the selection of appropriate local characteristic information for the Riau region plays a significant role in model performance and prediction results.

Several outcomes from the rainfall estimation modeling in this study hold practical value across various sectors. The identification of local characteristic variables influencing rainfall can serve as a foundation for anticipating the potential impacts of rainfall variability in specific areas. Additionally, the development of spatial rainfall estimation maps offers valuable insights for multiple sectors, including agriculture and plantations, tourism, and industry. Moreover, the findings related to the effect of principal component variables derived from GCM outputs provide critical information regarding the suitability of specific GCM models for rainfall prediction in Riau Province. These insights are particularly relevant to institutions such as the Meteorology, Climatology, and Geophysics Agency (BMKG) and other agencies involved in rainfall model verification and climate-related mitigation efforts.

#### 4. CONCLUSIONS

Based on the results, it can be concluded that the ESTF-VC model effectively addresses space-time autocorrelation in rainfall modeling. Beyond capturing space-time dependence, the model also enhances the overall performance of rainfall estimation. Among the local characteristic variables, only the equator variable exhibits a statistically significant local effect on rainfall patterns in Riau Province. In contrast, several principal components derived from GCM output data demonstrate a significant impact on rainfall variability. The model's predictive capability is satisfactory in certain time periods, where observed rainfall patterns are well replicated. However, discrepancies remain in other periods, indicating the need for further research to improve model accuracy and reliability. These inconsistencies may be attributed to the limited number of significant local characteristic variables or constraints in the spatial-temporal weight matrix used to capture dependency structures. This modeling framework remains open for further development, particularly

through modifications to the weight matrix used to define space-time dependency structures. In addition, incorporating additional local characteristic variables may enhance the model's ability to capture spatial and temporal variability in rainfall more accurately.

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### Author Contributions

D. A. M. contributed to the processes of Data collection, Analysis and Interpretation, Writing-reviewing and editing. A. D., A. H. W., and B. S. contributed to Conceptualization, Methodology, Review, and Supervision.

### Conflicts of Interest

The authors declare that there is no conflict of interest related to this article.

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## DECLARATION OF GENERATIVE AI

During the preparation of this work, the author(s) used DeepL and authentic QuillBot with a premium subscription to correct grammar and paraphrase some statements in the properly cited references. After using this tool/service, the author(s) reviewed and edited the content as needed and will take full responsibility for the content of the publication.

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