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Research Paper

Rainfall modeling with CMIP6-DCPP outputs and local characteristic information using eigenvector spatial filtering varying coefficient (ESF-VC)

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ABSTRACT

Estimating rainfall at a point or region is difficult because complex factors affect rainfall. A helpful strategy is to utilize the GCM output information from CMIP6-DCPP by forming a functional relationship between GCM output data and rainfall data at a certain point or region, called statistical downscaling. However, because the resolution of the GCM output is relatively low, the model could not explain the local effects since the heterogeneity is enormous. Based on this fact, the current research proposes to add some local characteristics in the downscaling model to improve the performance to predict the rainfall levels. Further, the rainfall levels have spatial dependencies among points. Therefore, this research employed the Eigenvector Spatial Filtering-Varying Coefficient (ESF-VC) as the methodology of the modeling. The objective of this research is to perform rainfall predictive modeling with CMIP6-DCPP output and some local characteristic information as predictors using ESF-VC methodology. The approach was implemented to predict the rainfall level in the Province of Riau in Indonesia. Based on the results, the ESF-VC model provides good performance in estimating rainfall in Riau. The variables that provide local effects are altitude, equator (location), equator (distance), and wet month dummy. While the variables ENSO and vegetation (NDVI) have a significant global effect on the model.

Keywords: Rainfall, CMIP6, DCPP, Eigenvector Spatial Filtering, Varying Coefficient

Rainfall is one measure that can provide benefits to various aspects of the environment. Rainfall is a measure of the height of rainwater collected in a rain gauge on a flat, non-absorbent, non-permeable, and non-flowing place (BMKG, 2023). But in fact, estimating rainfall in a location or region is quite difficult. This is due to several complex factors related to rainfall at a given location. Utilizing general circulation models (GCM) output information is one of the efforts that can be made to handle this. GCM is a numerical model that represents the physical atmosphere, oceans, cryosphere, and land surface that can be used to simulate global climate variables (IPCC, 2023). GCM data can be obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) with the Decadal Climate Prediction Project (DCPP) as one of the models. This model allows the coordination of climate predictions, predictability, and variability over decades (Boer *et al.*, 2016). The concept of utilizing GCM output for rainfall estimation is to form a functional relationship between GCM output data and rainfall data at a point or region called statistical downscaling (Wigena and Djuraidah, 2022). Goswami *et al*. (2024) evaluated the performance of 12 GCM-CMIP6 for rainfall and temperature of rice growing region of West Bengal, India and assigned weightage to each model based on their performance with observed data and climate projections data were used to assess its impact on crops (Mukherjee *et al.* 2024).

GCM output data simulates global climate variables spatially and temporally on each location grid measuring or . The low resolution causes GCM output data to be unable to explain local effects at points or regions that tend to be heterogeneous (Ratag, 2001). Based on these reasons, in addition to using GCM outputs, this study will also utilize some local characteristic information as a way to improve prediction accuracy. Some of the local information

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used is the height of the land surface, the state of vegetation, and the location of the observation point based on the equator. In addition, other information used is the El Niño-Southern Oscillation (ENSO) index and the wet month dummy.

Several studies have shown that rainfall in a region has spatial dependencies as well as variations in location and time effects (Djuraidah *et al*., 2019; Kardiana *et al*., 2022). This situation will disrupt several assumptions in the linear regression model such as the assumption of independence between observations and homogeneity. The independence assumption will fail to be met if there is a relationship between observations on the same variable called autocorrelation. Spatial autocorrelation can be measured using the Moran Coefficient (Mcoef) value. This measure forms the basis of the Eigenvector Spatial Filtering (ESF) model, one approach that can be used to handle spatial autocorrelation (Griffith, 2000). In addition to autocorrelation, rainfall data also allows for variations in location effects that are different for each observation point called spatial non-stationary (Fotheringham *et al*., 2002). The Spatial Varying Coefficient (SVC) model can be used to model non-stationary spatial effects between observation points. An ESF approach used to handle spatial autocorrelation has also been developed based on the SVC model (Murakami and Griffith, 2019) which will hereafter be referred to as the ESF-VC model.

The objectives of this study are (1) to conduct rainfall modeling based on CMIP6-DCPP output data and local characteristic information using the ESF-VC model, (2) to investigate and determine the global and local effects of predictor variables, and (3) to determine rainfall estimates based on the final model and analyze the coefficient of variation formed. The research location that will be the focus of this study is Riau province in Indonesia. The modeling results will be useful for estimating rainfall as well as analyzing the effects of local variables.

MATERIALS AND METHODS

Data source

The data used in this study were obtained from various sources with the period of 2015 to 2019. The Riau rainfall data in this study was obtained from the Meteorology, Climatology and Geophysics Agency (BMKG) and measured from 32 rainfall stations located throughout Riau (Fig. 1). The GCM output data used in this study were obtained from CMIP6-DCPP with the CNRM-ESM2 model and a 6 x 6 domain. In addition to rainfall and GCM data, this research also utilizes information on local characteristics in the research area. The first information used is the height of the rainfall measurement station location based on the height above sea level. The elevation of a location will correlate with the state of rainfall at that location (Lesik *et al.*, 2020). The next information is the vegetation index in the Riau region based on the normalized difference vegetation index (NDVI). Based on other research, the vegetation of an area is positively correlated with the state of rainfall (Kurnia and Agdialta, 2020; Sur *et al*., 2018). The Riau region, which is generally passed by the equator, has an equatorial rainfall type with the characteristics of having two peaks in the rainy season and generally occurs in March or October (Tukidin, 2010). Based on this, other local information is the distance and position of the rainfall measurement station to the equator. Equatorial distance is calculated based on the distance of coordinate points to the equator. Meanwhile, the position of the equator is determined with a dummy 0 for stations north of the equator and 1 for stations south of the equator.

In addition to local characteristic information, another variable used is the El Nino-Southern Oscillation (ENSO) index. This index is defined as sea surface temperature anomalies in the Pacific Ocean that can affect rainfall conditions in the Indonesian region (BMKG, 2024). The last variable used in this study is the wet month or rainy season dummy. This variable is obtained based on historical data with the wet month dummy period 1 and the other 0. Overall, the data and data sources used in this study are shown in Table 1.

In general, some modeling procedures that has been carried out include: (1) identify and overcome multicollinearity in GCM output data with Partial Least Square Regression (PLSR); (2) check the assumptions of autocorrelation and spatial heterogeneity;

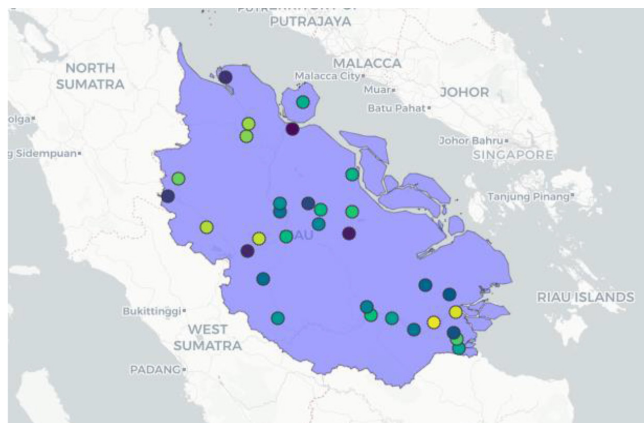

Fig. 1: Location of measurement stations and average monthly rainfall

Table 1: Data source

Research data	Data source
Rainfall observation data	Indonesian Meteorology, Climatology and Geophysics Agency (BMKG)
CMIP6-DCPP with CNRM-ESM2 model (36 grid)	https://esgf.llnl.gov/nodes.html
Altitude of rain station location	https://earth.google.com/web/
Normalized difference vegetation index (NDVI)	https://code.earthengine.google.com/
Station location based on the equator	https://earth.google.com/web/
El Nino-Southern Oscillation (ENSO) index	https://www.daculaweather.com/4_nino_graphs.php
Wet month dummy	Indonesian Meteorology, Climatology and Geophysics Agency (BMKG)

(3) perform ESF-VC modeling; (4) determine the local and global influence of predictor variables; and (5) estimate rainfall and analyze the variation of model coefficients.

Eigenvector spatial filtering (ESF)

One of the most popular measures used to quantify the degree of spatial autocorrelation is the Moran Coefficient (Mcoef). The form of Mcoef can be rewritten in matrix form as follows:

$$\frac{n}{\mathbf{1}'\boldsymbol{C}\mathbf{1}}\frac{\boldsymbol{Y}'\boldsymbol{MCMY}}{\boldsymbol{Y}'\boldsymbol{MY}} \qquad (1)$$

where is an n x n symmetric spatial weight matrix with n being the number of observations. The spatial weight matrix is determined based on the Euclid distance d_{ij} . Matrix $\boldsymbol{M}$ is a centering projection matrix that has a size of n x n with the form $M=(I-1(1'1)^{-1}1')$. While the matrix is an identity matrix with size n x n and is a vector of one size n x 1. ESF is built based on a linear combination of eigenvectors from the matrix based on Equation (1), especially in the numerator part, namely *MCM*. The set of eigenvectors of the MCM matrix is defined by $\boldsymbol{E}_{full} = \{\boldsymbol{e}_1, \dots, \boldsymbol{e}_n\}$ which expresses the map pattern based on the spatial dependency relationship. The decomposition of eigenvectors of the *MCM* matrix can be defined as $\boldsymbol{E}_{full}\boldsymbol{\Lambda}_{full}\boldsymbol{E}_{full}$ where $\boldsymbol{\Lambda}_{full}$ where is an n x n diagonal matrix for each kth element is an eigenvalue λ_k. The ESF linear model is defined as follows (Murakami & Griffith, 2015):

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{E\gamma} + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2\boldsymbol{I}) \qquad (2)$$

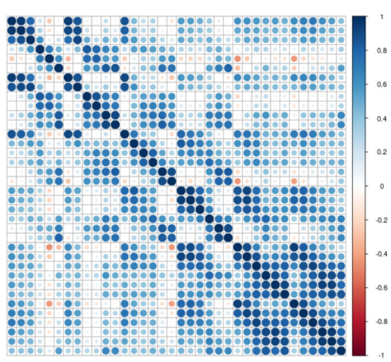

Fig. 2: Correlation plot from 36 grids

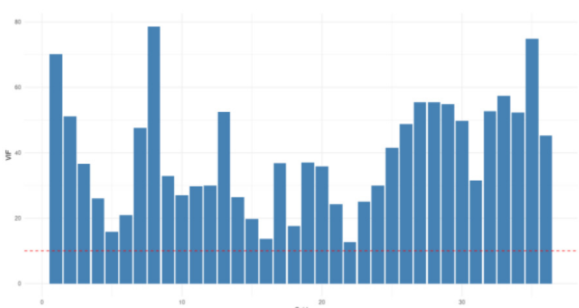

Fig. 3: Variance inflation factor (VIF) from 36 grids

Eigenvector spatial filtering – varying coefficient (ESF-VC)

The general form of the ESF-VC model can be defined as (Murakami & Griffith, 2019):

$$\boldsymbol{Y} = \beta_1\mathbf{1} + \boldsymbol{E}\gamma_1 + \sum_{p=2}^{P}\boldsymbol{X}_p \circ \boldsymbol{\beta}_p + \boldsymbol{\varepsilon} \quad \text{where } \boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2\boldsymbol{I}) \qquad (3)$$

The parameter βp is defined as:

$$\boldsymbol{\beta}_p = \beta_p\mathbf{1} + \boldsymbol{E\gamma}_p \qquad \text{where } \boldsymbol{\gamma}_p \sim N(\mathbf{0}_K, \sigma^2_{p(\gamma)}\boldsymbol{\Lambda}(\alpha_p))$$

Equation (3) is a form of ESF-VC involving the random effects of ESF-VC (RE ESF-VC) with is a zero vector of size K x 1, *E* is a matrix consisting of *K* eigenvectors based on positive eigenvalues $\sigma^2_{p(\gamma)}$ is the variance parameter and $\boldsymbol{\Lambda}(\alpha_p)$ is a K x K diagonal matrix with members at each k being k being $\lambda_k(\alpha_p) = (\sum_k \lambda_k / \sum_k \lambda_k^{\alpha_p})\lambda_k^{\alpha_p}$ (Murakami et al., 2018). The vector is a random coefficient that depends on two parameters $\sigma^2_{p(\gamma)}$ and αp.

RESULTS AND DISCUSSION

Multicollinearity diagnosis

This study uses CMIP6-DCPP GCM data of the CNRM-ESM2 model with a domain size of 6 x 6 and a total of 36 grids with a fairly high level of correlation between grids shown in Fig. 2. Based on the variance inflation factor (VIF) value (Fig. 3), all grids give VIF values of more than 10 (multicollinearity exists).

This research uses the partial least square regression (PLSR) approach to overcome multicollinearity. Selection of optimum PLSR components using the cross validation (CV) method

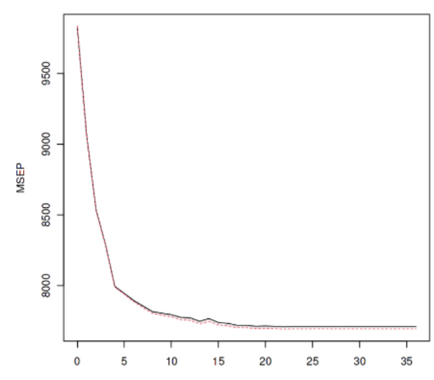

Fig. 4: Determination of optimal components

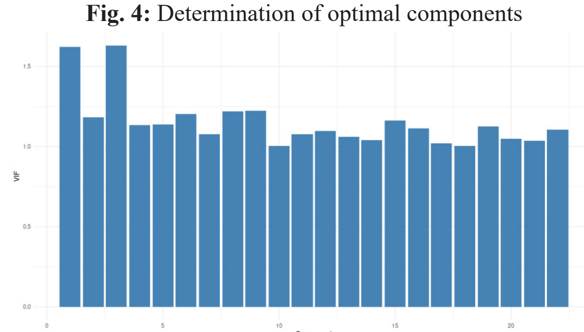

Fig. 5: Variance inflation factor (VIF) from 22 components

Table 2: Spatial autocorrelation and heteroscedasticity diagnosis

Diagnosis	Statistic test	*p-value*	Conclusion (Sig $p < 0.1$)
Spatial autocorrelation	Moran I test	0.01525	Reject
Heteroscedasticity	Breusch-Pagan test	0.00000	Reject

Table 3: Comparison of modeling results

Model	RMSE		AIC
OLS	85.28	0.25	22552.06
ESF	77.65	0.38	25855.71
ESF-VC	75.36	0.40	22337.06

Table 4: ESF-VC Coefficient Evaluation Results (without PC Score)

Coefficient	Sig ($p < 0.1$)		Effect Description
Intercept	1740/1920	91%	Local
ENSO	0/1920	0%	*
Altitude	660/1920	34%	Local
Vegetation (NDVI)	0/1920	0%	*
Equator (Location)	1380/1920	72%	Local
Equator (Distance)	600/1920	31%	Local
Wet month dummy	1440/1920	75%	Local

*) variables that will be explored further regarding the type of effect

based on the minimum mean squared error of prediction (MSEP) criteria with the results of the optimum components formed as many as 22 components (Fig. 4). The VIF value on the 22 components (Fig. 5) shows that all components have a VIF value of less than 10.

Spatial autocorrelation and spatial heteroscedasticity diagnosis

After multicollinearity is handled, the next step is to diagnose the presence or absence of spatial autocorrelation and heteroskesdacity with the results in Table 2. The results explain that there is spatial autocorrelation and spatial heteroskesdacity in the data. This result confirms that the ESF-VC model can be used to capture spatial effects in the research data.

Modeling results

Before modeling ESF-VC, to ensure that ESF-VC is a suitable model, a comparison of several models is conducted. The comparison results between the ordinary least square (OLS), eigenvector spatial filtering (ESF), and ESF-VC models are shown in Table 3. Based on the goodness of the model, the highest R^2 value is obtained in the ESF-VC model, which is 0.40. This indicates that the ESF-VC model can be used to model rainfall estimation in Riau with several predictor variables used. Based on the model error, ESF-VC shows the best results with the smallest RMSE value compared to OLS and ESF, which is 75.36. When viewed from the Akaike information criterion (AIC) value, the ESF-VC model provides the smallest AIC value of the other two models.

ESF-VC modeling results

In the initial modeling of ESF-VC, all predictor variables

Table 5: ESF-VC coefficient evaluation results (PLSR score only)

Percentage of locally significant coefficients (Sig $p < 0.1$)					
Comp1	1920/1920	100%	Comp12	1320/1920	69%
Comp2	1920/1920	100%	Comp13	1920/1920	100%
Comp3	1380/1920	72%	Comp14	360/1920	19%
Comp4	1920/1920	100%	Comp15	1920/1920	100%
Comp5	1920/1920	100%	Comp16	120/1920	6%
Comp6	1920/1920	100%	Comp17	1920/1920	100%
Comp7	1920/1920	100%	Comp18	120/1920	6%
Comp8	1920/1920	100%	Comp19	0/1920	0%
Comp9	960/1920	50%	Comp20	360/1920	19%
Comp10	1440/1920	75%	Comp21	0/1920	0%
Comp11	960/1920	50%	Comp22	660/1920	34%

Table 6: ESF-varying and non-varying coefficient results (without PC Score)

Coefficient		Sig ($p < 0.1$)		Effect description
Varying coefficient	Intercept	1920/1920	100%	Local
	Altitude	600/1920	31%	Local
	Equator (location)	1920/1920	100%	Local
	Equator (distance)	1680/1920	88%	Local
	Wet month dummy	480/1920	25%	Local
Non-varying coefficient	ENSO	1920/1920	100%	Global
	Vegetation (NDVI)	1920/1920	100%	Global

Table 7: Comparison ESF-VC and ESF-V&NVC

Model	RMSE		AIC
ESF-VC	75.36	0.40	22337.06
ESF-VC (V&N)	70.55	0.47	22089.26

are assumed to have local effects on rainfall. This assumption will then be tested to obtain the final model results. The ESF-VC modeling results are shown in Table 4 and Table 5.

Table 4 explains that the variables altitute, equator (location), equator (distance), and wet month dummy provide significant local effects. The other variables, ENSO and vegetation (NDVI) did not show a significant local effect. These two variables need to be explored further to confirm whether there is an effect in the model. In the evaluation of the ESF-VC PLSR Score coefficients shown in Table 5, there are 4 out of 22 PLSR scores that are assumed

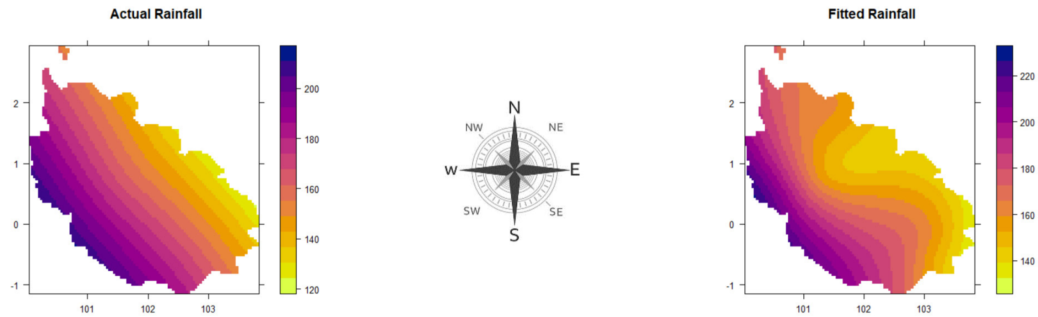

Fig. 6: Actual vs fitted rainfall

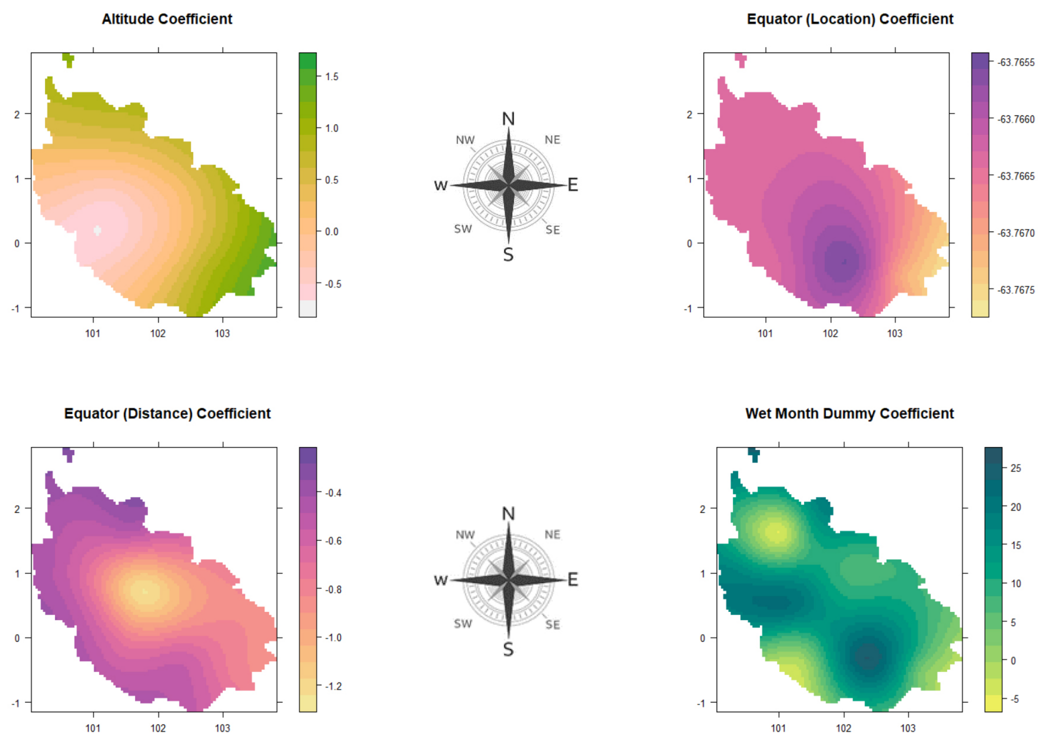

Fig. 7: Local variable coefficients

not to provide significant local effects in the model. The five PLSR scores are Comp16, Comp18, Comp19, and Comp21. The next step is to perform ESF-VC modeling with local and global variable settings. Based on the results obtained, the variables assumed to have local effects are altitute, equator (location), equator (distance), and wet month dummy. While the variables assumed to have global effects are ENSO and vegetation (NDVI). This process aims to confirm whether the variables ENSO and vegetation (NDVI) have a global effect or not.

ESF-VC modeling results (varying and non-varying coefficient)

ESF-VC modeling with varying and non-varying coefficient (ESF-V&NVC) settings aims to investigate whether a predictor variable has a local, global, or no effect in the model. In this section, the focus variable to be investigated is the variable without PLSR Score with the results shown in Table 6. After setting the varying and non-varying coefficient based on Table 6, the variables altitude, equator (location), equator (distance), and wet month dummy still have a local effect on the model.

Other information obtained is that the variables ENSO and vegetation (NDVI) have a significant global influence on the model. This result indicates that the influence of ENSO and vegetation (NDVI) is the same for each location point. In addition, this result confirms that vegetation in Riau tends to be homogeneous based on the effect of rainfall.

When viewed from the goodness of the model based on the value from Table 7, the ESF-V&NVC model shows better performance than the ESF-VC model. This is also in line with the results in the evaluation of model errors that show the RMSE value of ESF-V&NVC is smaller than ESF-VC as well as the AIC value. These results show that setting varying and non-varying coefficient can improve the accuracy and goodness of the model.

The comparison of actual rainfall and fitted rainfall is shown in Figure 6 with yellow color representing low rainfall and purple color representing high rainfall. Based on these results, the fitted rainfall distribution pattern for the Riau region has similar characteristics to the actual rainfall. Rainfall in the southwestern part of Riau tends to be higher than in the northeastern region. These two locations show quite contrasting color differences. Both areas are coastal areas directly adjacent to the Indian Ocean in the southwest and the Malacca Strait in the northeast. The darker colors on the map represent increasingly larger coefficients and the lighter colors represent increasingly smaller coefficients. In the Altitude variable, the coefficient formed has a range from (-) to (+). This shows that Altitude has both negative and positive effects on rainfall. The altitude factor which has a dark green color tends to have a positive effect on rainfall. This means that areas with high altitude have high levels of rainfall and vice versa. While light-colored areas have a negative effect on rainfall, meaning that areas with high elevation have low rainfall levels and vice versa. The results on the Altitude variable coefficient show that in the Riau region, the rainfall that occurs is not dominated by certain Altitude conditions. This can be caused because 32 measurement stations are at an altitude between 3 to 85 meters from sea level or lowland category.

The coefficient on the equator variable (location) shows a value with a sign (-). This means that areas south of the equator tend to have a low effect on rainfall. While in the equator variable (distance), the coefficient formed has a sign (-) which means that the closer an area is to the equator, the higher the rainfall that will occur. In the wet month dummy variable, the coefficient formed has a sign (-) and (+) which means that some regions have a peak rainy season or wet month that is different from other regions.

CONCLUSIONS

Based on the results and discussion, several conclusions can be drawn from the research that has been conducted. In general, the ESF-VC model provides good performance in estimating rainfall in Riau. Setting local and global effects on the ESF-VC model can improve the performance of the modeling results. The variables altitude, equator (location), equator (distance), and wet month dummy provide local effects on the model. While the variables ENSO and vegetation (NDVI) have a significant global effect on the model. Based on the rainfall pattern of the ESF-VC model, the rainfall estimation results have a similar pattern to the actual rainfall. The variation in the coefficients obtained indicates that variables with local effects have different impacts on rainfall at each location or region.

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Data availability: The available data are monthly precipitation output of DCPP model obtained from Earth System Grid Federation (ESGF), location characteristic information from Google and El Nino-Southern Oscillation information.

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

Author contribution: **D. A. Mahkya**: Data collection, Analysis and Interpretation, Writing-review and editing; **A. Djuraidah**: Conceptualization, Methodology, Writing-review, Supervision; **A. H. Wigena**: Methodology, Writing-review, Supervision; **B. Sartono**: Methodology, Writing-review, Supervision.

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