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Research paper

Location Weight of GSTAR Model for High Variability of Rainfall Data

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Abstract

The use of location weights in the spatio temporal models took part in the accuracy of the model. The weights that often used are uniform weight, inverse distance weight, and normalized cross-correlation weight. These location weights consider the closeness between locations. For data that have high degree of variability, the use of these location weights becomes less relevant. Therefore, it is necessary to consider variability aspects of observational data as the location weights, that is the normalize ratio variance weight. The study was conducted to develop GSTAR-SUR model with normalize ratio variance weight and its application on rainfall data. The data used is ten daily rainfall data in the region Blimbing, Singosari, Karangploso, Dau, and Wagir. Based on the results of the study, indicated that the GSTAR-SUR ((1) (1,2,3,12,36) model that used ratio variance as location weight are more accurately to forecast the rainfall data that has high variability and extreme point.

Keywords: *GSTAR-SUR, rainfall, ratio variance*

1. Introduction

Spatio-temporal models that have been developed were Space-Time Autoregressive (STAR) introduced by Pfeifer and Deutsch (1980), Generalized Space-Time Autoregressive (GSTAR) and GSTAR-OLS developed by Ruchjana (2001 and 2002). The latest development of spatio-temporal models are GSTAR-SUR developed by Iriany (2013) to address the non stationary data and seasonal pattern.

The use of weights locations to form spatio temporal models also contribute to the accuracy of the model. The weights that often used are uniform weight, inverse distance weight, and normalized cross-correlation weight. (Suhartono and Atok, 2006; Suhartono and Subanar, 2006). The weight of these locations considering the closeness between locations. For data that have high variability, the use of location weights mentioned above becomes less relevant. The novelty of this study is the use of location weight that suitable for high variability data. Therefore, this study was conducted to assess the models of spatio temporal using normalization of ratio variance weight for high variability data.

2. Research Design

This study uses secondary data derived from 10 daily rainfall data that obtained from the rain post of Blimbing, Karangploso, Singosari, Wagir, and Dau region. The period of data used is January 2001 to December 2014, in which the data from January 2001 to December 2013 is used to conduct training (in-sample). The data from January to December 2014 is used as data testing (out-sample). GSTAR-SUR parameter estimation begins with a weighted normalized cross correlation. Then proceed with the establishment of GSTAR-SUR using normalization ratio-variance weight and compare these two models predicted results in the data testing. Software that used are R, Minitab and SAS.

2.1. Material and Methods

Generalized Space Time Autoregressive (GSTAR) is a new model for time series data. Ruchjana (2002) suggested that GSTAR is a generalization and extension model of Space Time Autoregressive (STAR) from Pfeifer (1979). GSTAR is more realistic because more prevalent models with different model parameters for different locations (Wuthqa and Suhartono, 2009). GSTAR model order p and spatial order $\lambda_1, \lambda_2, ..., \lambda_p$, GSTAR $(p\lambda_1, \lambda_2, ..., \lambda_p)$ formulated as follows (Borovkova, Lopuhaa and Nurani, 2002):

$$\mathbf{Z}_t = \boldsymbol{\mu}(t) + \sum_{k=1}^{p}\left[\boldsymbol{\Phi}_{k0} + \sum_{m=1}^{\lambda_k}\boldsymbol{\Phi}_{kl} w^{(l)}\right]\mathbf{Z}_{(t-p)} + \boldsymbol{\varepsilon}(t) \quad (1)$$

where:

$\mathbf{\Phi}_{k0} = \mathrm{diag}(\phi_{k0}^{(1)},...,\phi_{k0}^{(N)})$ dan $\mathbf{\Phi}_{kl} = \mathrm{diag}(\phi_{kl}^{(1)},...,\phi_{kl}^{(N)})$

The weight is chosen so that $w_{ii} = 0$ and $\sum_{i \neq j} w_{ij} = 1$

Seemingly Unrelated Regression (SUR) is an equation that parameter estimation using General Least Square (GLS). Iriany (2013) explains that GLS is the regression coefficient estimator that takes the relationship between error of equations, the error values are obtained from Ordinary Least Square (OLS) that will be used in the calculation of the regression coefficients to estimate the equation system SUR. SUR models with M equation expressed by

$$\boldsymbol{y_i} = \boldsymbol{X_i \beta_i} + \boldsymbol{\varepsilon_i}, \quad i = 1, \dots, N \qquad (2)$$

where $\boldsymbol{y_i}$ is vector with size $R\times 1$, X_i with size $R\times k_i$ dan β_i vector with size $k_i \times 1$. Equation system (4) can be written to the matrices :

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_N \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{pmatrix} = X\beta + \varepsilon$$

According to Greene (2002), equation (4) is a model SUR under the assumption $E\left[\varepsilon \middle| \boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_N}\right] = 0$ and $E\left[\varepsilon\varepsilon' \middle| \boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_N}\right] = \boldsymbol{\Omega}$ with $\boldsymbol{\Omega}$ is variance-covariance matrice.

GLS method using the error variance, ie :

$\mathrm{Cov}(\varepsilon) = \mathrm{E}(\varepsilon\varepsilon') = \sigma^2\boldsymbol{\Sigma} = \boldsymbol{\Omega}$

Matrice of $\boldsymbol{\Omega}$ describe the relation between the errors:

$$\boldsymbol{\Omega} = \mathrm{E}(\varepsilon\varepsilon') = \begin{bmatrix} \mathrm{E}(e_1 e_1') & \mathrm{E}(e_1 e_2') & \cdots & \mathrm{E}(e_1 e_N') \\ \mathrm{E}(e_2 e_1') & \mathrm{E}(e_2 e_2') & \cdots & \mathrm{E}(e_2 e_N') \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{E}(e_N e_1') & \mathrm{E}(e_N e_2') & \cdots & \mathrm{E}(e_N e_N') \end{bmatrix}$$

since $E(\varepsilon_i \varepsilon_j') = \sigma_{ij} I_T$ that:

$$\boldsymbol{\Omega} = \begin{bmatrix} \sigma_{11}\mathbf{I}_{NT} & \sigma_{12}\mathbf{I}_{NT} & \cdots & \sigma_{1N}\mathbf{I}_{NT} \\ \sigma_{21}\mathbf{I}_{NT} & \sigma_{22}\mathbf{I}_{NT} & \cdots & \sigma_{2N}\mathbf{I}_{NT} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1}\mathbf{I}_{NT} & \sigma_{N2}\mathbf{I}_{NT} & \cdots & \sigma_{NN}\mathbf{I}_{NT} \end{bmatrix} = \boldsymbol{\Sigma} \otimes \mathbf{I}_{NT}$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1m} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1} & \sigma_{m2} & \cdots & \sigma_{mm} \end{bmatrix} \qquad (3)$$

with $\mathbf{I}_{NT}$ is identity matrice with size $(NT \times NT)$ and $\boldsymbol{\Sigma}$ is matrice with size $(N \times N)$ and σ_{ij} is variance of error from each equation for $i = j$ and covariance of error between the equation for $i \neq j$.

Model parameters estimation is obtained with the suspect parameter $\boldsymbol{\beta}$ in equation (2).

$$\begin{aligned} \boldsymbol{\varepsilon_*' \varepsilon_*} &= \boldsymbol{\varepsilon' \Omega^{-1} \varepsilon} \\ &= \boldsymbol{Y'\Omega^{-1}Y - 2Y'\Omega^{-1}X\beta + \beta'X'\Omega^{-1}X\,\beta} \end{aligned} \qquad (4)$$

Equation (4) derived to the $\boldsymbol{\beta}$ and equated to be zero.

So that :

$$(\boldsymbol{X'\Omega^{-1}X})\boldsymbol{\hat{\beta}} = \boldsymbol{X'\Omega^{-1}Y}$$

$$(\boldsymbol{X'\Omega^{-1}X})^{-1}(\boldsymbol{X'\Omega^{-1}X})\boldsymbol{\hat{\beta}} = (\boldsymbol{X'\Omega^{-1}X})^{-1}\boldsymbol{X'Y}$$

$$\boldsymbol{I\hat{\beta}} = (\boldsymbol{X'\Omega^{-1}X})^{-1}\boldsymbol{X'\Omega^{-1}Y}$$

$$\boldsymbol{\hat{\beta}} = (\boldsymbol{X'\Omega^{-1}X})^{-1}\boldsymbol{X'\Omega^{-1}Y} \qquad (5)$$

Estimator of $\boldsymbol{\beta}$ for GSTAR-SUR (p1) model is follow:

$$\begin{aligned} \boldsymbol{\hat{\beta}} &= (\boldsymbol{X'\Omega^{-1}X})^{-1}\boldsymbol{X'\Omega^{-1}Y} \\ &= (X'(\hat{\boldsymbol{\Sigma}}^{-1} \otimes \mathbf{I}_{NT})X)^{-1}X'(\hat{\boldsymbol{\Sigma}}^{-1} \otimes \mathbf{I}_{NT})\mathbf{Y} \end{aligned} \qquad (6)$$

3. Data and Findings

The following statistical description rainfall data at the five locations are presented in Table 1:

Table 1: The Description of Rainfall Data at Each Location

Location	N	Mean (mm)	Standard Deviation (mm)	Minimum (mm)	Maximum (mm)
Blimbing	360	5.682	6.909	0	33.5
Singosari	360	3.93	5.575	0	41.75
Karangploso	360	4.302	5.71	0	25.36
Dau	360	4.564	5.825	0	36.38
Wagir	360	7.08	8.187	0	43.63

Based on Table 1 shows that rainfall at each location has a high variability. It can be seen from the standard deviation greater than the average. High variability indicates the fluctuation to the point of extreme rainfall, especially during the rainy season. Here is the results of testing homogeneity of variance of rainfall data:

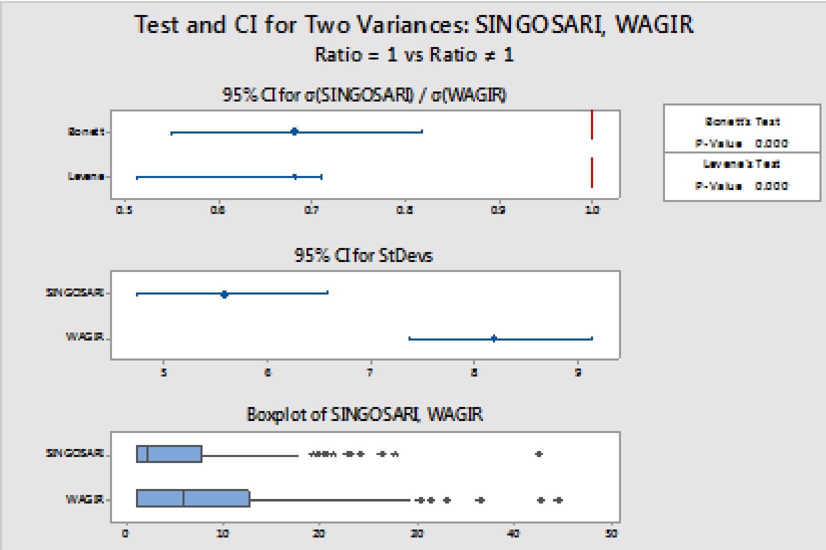

Fig 1: Homogeneity Test of Variance of Rainfall Data

Based on Figure 1 the results of testing the homogeneity of variance using Bartlett test and Levene test was obtained p-value 0.000 (p <0.05), indicate that the rainfall data at Blimbing, Karangploso, Singosari, Wagir, and Dau has different variance. Based on research data, obtained time series plot as follows:

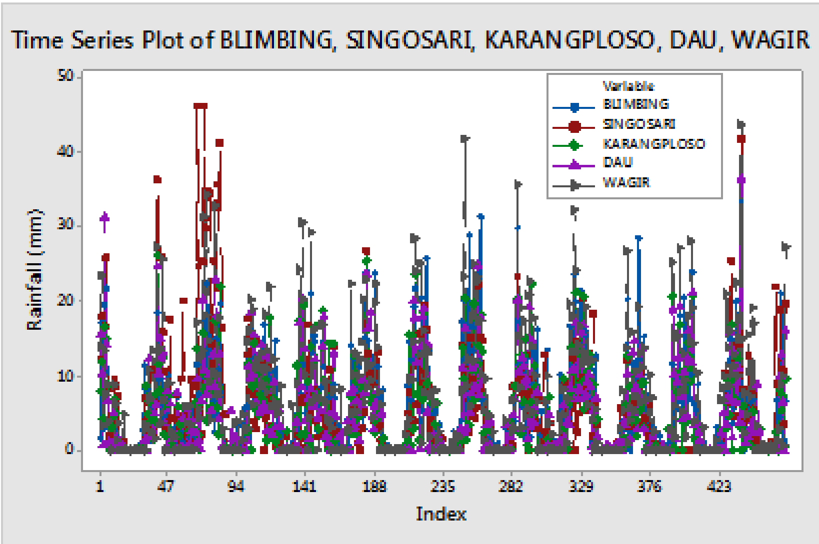

Fig 2: Time Series Plots Rainfall at Blimbing, Singosari, Karangploso, Dau, and Wagir

Based on Figure 2 note that the movement patterns of rainfall data at five locations are relatively the same, but Singosari region has higher rainfall. Identification model is done by comparing the AIC value at some time lag. Here the AIC value with VARMAX procedure in SAS:

Table 2: AIC Value

Order	AIC Value
1	14.67906
2	14.52868
3	14.52445

Based on Table 1, the lowest AIC is at 3rd order. Thus, the GSTAR order used is GSTAR (1,2,3). Identification of the seasonal rainfall data carried out by ACF and PACF plots at each location. Based on ACF plot indicated that the rainfall data at each location has seasonal patterns. This can be seen in the ACF plot that has a repeated pattern in a certain time lag. Based on PACF plot has indicated that there is some time lag PACF which cross the boundary line 5%. It concluded at 5 locations, all of locations have PACF the time lag of 12 and 36. Therefore, the identification of seasonal patterns indicated that the appropriate model is GSTAR ((1) (1,2,3,12,36)). The normalized cross-correlation weight is as follows:

$$W_{ij} = \begin{bmatrix} 0 & 0.2353 & 0.2294 & 0.2688 & 0.2665 \\ 0.2664 & 0 & 0.2143 & 0.2675 & 0.2518 \\ 0.2734 & 0.2100 & 0 & 0.2765 & 0.2401 \\ 0.2950 & 0.2174 & 0.2327 & 0 & 0.2549 \\ 0.2694 & 0.2235 & 0.2420 & 0.2650 & 0 \end{bmatrix}$$

While the normalize ratio-variance weight are as follows:

$$W_{ij} = \begin{bmatrix} 0 & 0.189 & 0.198 & 0.206 & 0.407 \\ 0.263 & 0 & 0.180 & 0.187 & 0.370 \\ 0.266 & 0.173 & 0 & 0.189 & 0.373 \\ 0.268 & 0.174 & 0.183 & 0 & 0.376 \\ 0.328 & 0.214 & 0.224 & 0.233 & 0 \end{bmatrix}$$

Based on the results of parameter estimation, GSTAR-SUR ((1) (1,2,3,12,36)) model with normalized cross-correlation weight for each location are as follows:

Forecast Model at Blimbing :

$$\hat{Z}_{1t} = 0.119 Z_{1(t-1)} + 0.009 Z_{2(t-1)} - 0.009 Z_{3(t-1)} + 0.022 Z_{4(t-1)} + 0.017 Z_{5(t-1)} + 0.205 Z_{1(t-2)} + 0.087 Z_{2(t-2)} + 0.084 Z_{3(t-2)} + 0.009 Z_{4(t-2)} + 0.075 Z_{5(t-2)} - 0.086 Z_{1(t-3)} - 0.074 Z_{2(t-3)} + 0.037 Z_{3(t-3)} + 0.023 Z_{4(t-3)} + 0.005 Z_{5(t-3)} + 0.059 Z_{1(t-12)} - 0.056 Z_{2(t-12)} - 0.01 Z_{3(t-12)} + 0.019 Z_{4(t-12)} - 0.025 Z_{5(t-12)} + 0.246 Z_{1(t-36)} + 0.052 Z_{2(t-36)} - 0.093 Z_{3(t-36)} + 0.034 Z_{4(t-36)} + 0.069 Z_{5(t-36)}$$

Forecast Model at Singosari :

$$\hat{Z}_{2t} = 0.024 Z_{1(t-1)} + 0.171 Z_{2(t-1)} - 0.009 Z_{3(t-1)} + 0.02 Z_{4(t-1)} + 0.012 Z_{5(t-1)} + 0.017 Z_{1(t-2)} - 0.255 Z_{2(t-2)} + 0.083 Z_{3(t-2)} + 0.009 Z_{4(t-2)} + 0.052 Z_{5(t-2)} + 0.055 Z_{1(t-3)} + 0.649 Z_{2(t-3)} + 0.036 Z_{3(t-3)} + 0.021 Z_{4(t-3)} + 0.004 Z_{5(t-3)} - 0.017 Z_{1(t-12)} + 0.335 Z_{2(t-12)} - 0.01 Z_{3(t-12)} + 0.018 Z_{4(t-12)} - 0.018 Z_{5(t-12)} + 0.031 Z_{1(t-36)} - 0.084 Z_{2(t-36)} - 0.092 Z_{3(t-36)} + 0.031 Z_{4(t-36)} + 0.048 Z_{5(t-36)}$$

Forecast Model at Karangploso :

$$\hat{Z}_{3t} = 0.033 Z_{1(t-1)} + 0.008 Z_{2(t-1)} + 0.411 Z_{3(t-1)} + 0.023 Z_{4(t-1)} + 0.016 Z_{5(t-1)} + 0.023 Z_{1(t-2)} + 0.081 Z_{2(t-2)} - 0.318 Z_{3(t-2)} + 0.01 Z_{4(t-2)} + 0.072 Z_{5(t-2)} + 0.076 Z_{1(t-3)} - 0.069 Z_{2(t-3)} - 0.056 Z_{3(t-3)} + 0.024 Z_{4(t-3)} + 0.005 Z_{5(t-3)} - 0.023 Z_{1(t-12)} - 0.052 Z_{2(t-12)} + 0.029 Z_{3(t-12)} + 0.02 Z_{4(t-12)} - 0.024 Z_{5(t-12)} + 0.042 Z_{1(t-36)} + 0.048 Z_{2(t-36)} + 0.752 Z_{3(t-36)} + 0.035 Z_{4(t-36)} + 0.066 Z_{5(t-36)}$$

Forecast Model at Dau :

$$\hat{Z}_{4t} = 0.033 Z_{1(t-1)} + 0.009 Z_{2(t-1)} - 0.009 Z_{3(t-1)} + 0.253 Z_{4(t-1)} + 0.016 Z_{5(t-1)} + 0.023 Z_{1(t-2)} + 0.089 Z_{2(t-2)} + 0.086 Z_{3(t-2)} + 0.13 Z_{4(t-2)} + 0.069 Z_{5(t-2)} + 0.076 Z_{1(t-3)} - 0.075 Z_{2(t-3)} + 0.038 Z_{3(t-3)} + 0 Z_{4(t-3)} + 0.005 Z_{5(t-3)} - 0.023 Z_{1(t-12)} - 0.057 Z_{2(t-12)} - 0.01 Z_{3(t-12)} - 0.119 Z_{4(t-12)} - 0.023 Z_{5(t-12)} + 0.042 Z_{1(t-36)}) + 0.053 Z_{2(t-36)} - 0.096 Z_{3(t-36)} + 0.169 Z_{4(t-36)} + 0.064 Z_{5(t-36)}$$

Forecast Model at Wagir :

$$\hat{Z}_{5t} = 0.031 Z_{1(t-1)} + 0.009 Z_{2(t-1)} - 0.01 Z_{3(t-1)} + 0.023 Z_{4(t-1)} + 0.243 Z_{5(t-1)}) + 0.022 Z_{1(t-2)} + 0.092 Z_{2(t-2)} + 0.092 Z_{3(t-2)} + 0.01 Z_{4(t-2)} + 0.07 Z_{5(t-2)} + 0.072 Z_{1(t-3)} - 0.078 Z_{2(t-3)} + 0.04 Z_{3(t-3)} + 0.024 Z_{4(t-3)} + 0.048 Z_{5(t-3)} - 0.022 Z_{1(t-12)} - 0.059 Z_{2(t-12)} - 0.011 Z_{3(t-12)} + 0.02 Z_{4(t-12)} + 0.047 Z_{5(t-12)} + 0.04 Z_{1(t-36)} + 0.055 Z_{2(t-36)} - 0.102 Z_{3(t-36)} + 0.035 Z_{4(t-36)} + 0.206 Z_{5(t-36)}$$

There are GSTAR-SUR ((1)(1,2,3,12,36)) model with ratio-variance for each location :

Forecast Model at Blimbing :

$$Z_{1t} = 0.053 Z_{1(t-1)} - 0.018 Z_{2(t-1)} + 0.004 Z_{3(t-1)} + 0.028 Z_{4(t-1)} + 0.014 Z_{5(t-1)} + 0.229 Z_{1(t-2)} + 0.097 Z_{2(t-2)} + 0.073 Z_{3(t-2)} + 0.018 Z_{4(t-2)} + 0.144 Z_{5(t-2)} - 0.197 Z_{1(t-3)} - 0.071 Z_{2(t-3)} + 0.036 Z_{3(t-3)} + 0.035 Z_{4(t-3)} - 0.011 Z_{5(t-3)} + 0.129 Z_{1(t-12)} - 0.026 Z_{2(t-12)} - 0.038 Z_{3(t-12)} + 0.012 Z_{4(t-12)} - 0.025 Z_{5(t-12)} + 0.189 Z_{1(t-36)} + 0.05 Z_{2(t-36)} - 0.057 Z_{3(t-36)} + 0.022 Z_{4(t-36)} + 0.119 Z_{5(t-36)}$$

Forecast Model at Singosari :

$$Z_{2t} = 0.045 Z_{1(t-1)} + 0.357 Z_{2(t-1)} + 0.003 Z_{3(t-1)} + 0.026 Z_{4(t-1)} + 0.013 Z_{5(t-1)} + 0.01 Z_{1(t-2)} - 0.478 Z_{2(t-2)} + 0.066 Z_{3(t-2)} + 0.017 Z_{4(t-2)} + 0.131 Z_{5(t-2)} + 0.094 Z_{1(t-3)} + 0.765 Z_{2(t-3)} + 0.033 Z_{3(t-3)} + 0.032 Z_{4(t-3)} - 0.01 Z_{5(t-3)} - 0.038 Z_{1(t-12)} + 0.179 Z_{2(t-12)} - 0.034 Z_{3(t-12)} + 0.011 Z_{4(t-12)} - 0.023 Z_{5(t-12)} + 0.042 Z_{1(t-36)} - 0.153 Z_{2(t-36)}) - 0.051 Z_{3(t-36)} + 0.02 Z_{4(t-36)} + 0.108 Z_{5(t-36)}$$

Forecast Model at Karangploso :

$Z_{3t} = 0.045\ Z_{1(t-1)} - 0.016\ Z_{2(t-1)} + 0.352\ Z_{3(t-1)} + 0.026\ Z_{4(t-1)} + 0.013\ Z_{5(t-1)} + 0.01\ Z_{1(t-2)} + 0.089\ Z_{2(t-2)} - 0.349\ Z_{3(t-2)} + 0.017\ Z_{4(t-2)} + 0.132\ Z_{5(t-2)} + 0.095\ Z_{1(t-3)} - 0.065\ Z_{2(t-3)} - 0.086\ Z_{3(t-3)} + 0.032\ Z_{4(t-3)} - 0.01\ Z5(t-3) - 0.039\ Z1(t-12) - 0.024\ Z_{2(t-12)} + 0.216\ Z_{3(t-12)} + 0.011\ Z_{4(t-12)} - 0.023\ Z_{5(t-12)} + 0.042\ Z_{1(t-36)} + 0.046\ Z_{2(t-36)} + 0.63\ Z_{3(t-36)} + 0.02\ Z_{4(t-36)} + 0.109\ Z_{5(t-36)}$

Forecast Model at Dau :

$Z_{4t} = 0.045\ Z_{1(t-1)} - 0.017\ Z_{2(t-1)} + 0.003\ Z_{3(t-1)} + 0.192\ Z_{4(t-1)} + 0.013\ Z_{5(t-1)} + 0.01\ Z_{1(t-2)} + 0.09\ Z_{2(t-2)} + 0.067\ Z_{3(t-2)} + 0.058\ Z_{4(t-2)} + 0.133\ Z_{5(t-2)} + 0.096\ Z_{1(t-3)} - 0.065\ Z_{2(t-3)} + 0.033\ Z_{3(t-3)} - 0.084\ Z_{4(t-3)} - 0.01\ Z_{5(t-3)} - 0.039\ Z_{1(t-12)} - 0.024\ Z_{2(t-12)} - 0.035\ Z3(t-12) - 0.11\ Z4(t-12) - 0.023\ Z5(t-12) + 0.042\ Z1(t-36) + 0.046\ Z_{2(t-36)} - 0.052\ Z_{3(t-36)} + 0.179\ Z_{4(t-36)} + 0.109\ Z_{5(t-36)}$

Forecast Model at Wagir :

$Z_{5t} = 0.056\ Z_{1(t-1)} - 0.02\ Z_{2(t-1)} + 0.004\ Z_{3(t-1)} + 0.032\ Z_{4(t-1)} + 0.266\ Z5(t-1) + 0.012\ Z_{1(t-2)} + 0.11\ Z_{2(t-2)} + 0.083\ Z_{3(t-2)} + 0.021\ Z_{4(t-2)} - 0.002\ Z_{5(t-2)} + 0.117\ Z_{1(t-3)} - 0.08\ Z_{2(t-3)} + 0.041\ Z_{3(t-3)} + 0.04\ Z_{4(t-3)} + 0.087\ Z_{5(t-3)} - 0.048\ Z_{1(t-12)} - 0.03\ Z_{2(t-12)} - 0.043\ Z_{3(t-12)} + 0.014\ Z_{4(t-12)} + 0.029\ Z_{5(t-12)} + 0.052\ Z_{1(t-36)} + 0.057\ Z_{2(t-36)} - 0.064\ Z_{3(t-36)} + 0.025\ Z_{4(t-36)} + 0.153\ Z_{5(t-36)}$

Table 4: Validation Test of GSTAR-SUR ((1)(1,2,3,12,36)) Model

Location	Model with Cross-Correlation Weight		Model with Ratio-Variance Weight	
	t-statistic	**p-value**	**t-statistic**	**p-value**
Blimbing	0.491	0.626	0.546	0.588
Singosari	0.827	0.414	1.363	0.182
Karangploso	2.689	0.011*	3.064	0.004*
Dau	-0.505	0.617	0.743	0.463
Wagir	1.610	0.116	0.474	0.638

Based on the results of the validation test GSTAR-SUR ((1) (1,2,3,12,36)) using the paired t test, at $\alpha = 5\%$, Blimbing, Singosari, Dau, and Wagir have p-value that more than 0.05 in which showed no significant difference between the actual data rainfall with forecast results. From these tests indicated that both models have a high degree of accuracy in predicting precipitation, especially in Blimbing, Singosari, Dau, and Wagir. While Karangploso has a p-value less than 0.05 which indicates that there are significant differences between the actual rainfall data with forecast results. Comparison of the accuracy GSTAR-SUR ((1) (1,2,3,12,36)) which built with normalized cross-correlation weight with the ratio-variance weight can be seen from the both RMSE and R2 prediction models that presented in the following table:

Table 5: Comparison of The Accuracy GSTAR-SUR ((1)(1,2,3,12,36)) Model

Location	Model with Cross-Correlation Weight			Model with Ratio-Variance Weight		
	RMSE Data Training	**RMSE Data Testing**	**R^2prediction**	**RMSE Data Training**	**RMSE Data Testing**	**R^2prediction**
Blimbing	5.796	10.471	0.579	5.792	10.485	0.618
Singosari			0.609			0.691
Karangploso			0.707			0.615
Dau			0.565			0.494
Wagir			0.328			0.444

Based on the comparison of accuracy GSTAR-SUR ((1) (1,2,3,12,36)) model that used normalized cross-correlation weight with the ratio-variance weight indicated that Blimbing, Singosari, and Wagir, the models with ratio-variance weight have more accurate forecasts. It can be seen from the value of R2 prediction that higher than models used normalized cross-correlation weight. While on location Karangploso and Dau, model with normalized cross-correlation weight are superior in producing more accurate forecasts. From this test proved that the use of normalized ratio-variance weights has an advantage in predicting rainfall data that has a high degree of variability and had extreme point.

4. Conclusion

This study compared two GSTAR-SUR models built from two different location weights, ie normalization of cross-correlation weights with ratio variance weight. Rainfall data at 5 locations has a high variability. This is shown from the standard deviation value higher than the average value. From the 5 sites studied, the highest level of diversity was obtained at the Wagir site as indicated by the highest standard deviation score compared to the other locations. Based on the results of this study concluded that the weight ratio-variance to build GSTAR-SUR ((1) (1,2,3,12,36) model has better forecast for high variability and extremes rainfall data.

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