International Journal of Engineering & Technology, 8 (1.9) (2019) 166-171

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Location Weight of GSTAR Model for High Variability of Rainfall Data

Agus Dwi Sulistyono, Waego Hadi Nugroho, Atiek Iriany*

Department of Statistics, Faculty of Mathematics and Natural Sciences Brawijaya University, Malang
**Corresponding author E-mail: agus.dwi.sulistyono@gmail.com*

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):

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

Copyright © 2019 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

where:

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

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

$$\boldsymbol{y_i} = \boldsymbol{X_i}\boldsymbol{\beta_i} + \boldsymbol{\varepsilon_i}, \quad i = 1, ..., N \tag{2}$$

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 :

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

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

GLS method using the error variance, ie :

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

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

$$\boldsymbol{\Omega} = \text{E}(\varepsilon\varepsilon') = \begin{bmatrix} \text{E}(e_1e_1') & \text{E}(e_1e_2') & \cdots & \text{E}(e_1e_N') \\ \text{E}(e_2e_1') & \text{E}(e_2e_2') & \cdots & \text{E}(e_2e_N') \\ \vdots & \vdots & \ddots & \vdots \\ \text{E}(e_Ne_1') & \text{E}(e_Ne_2') & \cdots & \text{E}(e_Ne_N') \end{bmatrix}$$

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

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

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

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).

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

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

So that :

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

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

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

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

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

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

$$= \boldsymbol{(X'(\hat{\Sigma}^{-1} \otimes \mathbf{I}_{NT})X)^{-1}X'(\hat{\Sigma}^{-1} \otimes \mathbf{I}_{NT})Y} \tag{6}$$

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:

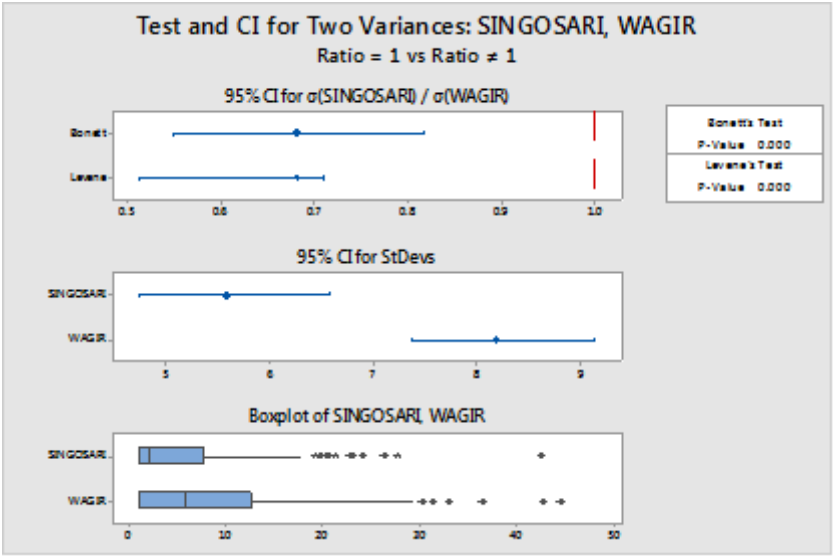


Fig 1: Homogeneity Test of Variance of Rainfall Data

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:

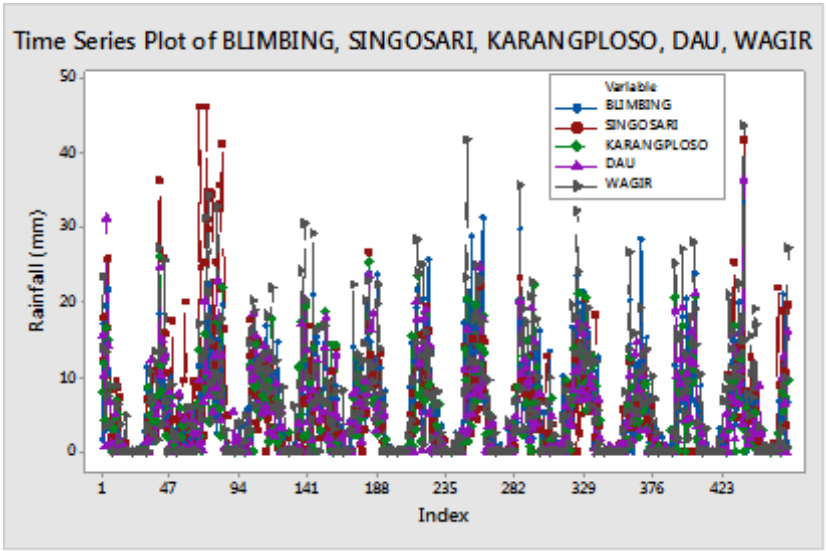


Fig 2: Time Series Plots Rainfall at Blimbing, Singosari, Karangploso, Dau, and Wagir

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.

References

[1] Borovkova, S.A., Lopuha, H.P. and Ruchjana, B.N. 2002. Generalized S-TAR with Random Weights. Proceeding of the 17th International Workshop on Statistical Modeling. Chania-Greece.

[2] Davidson, Russell and MacKinnon, James G. 1993. Estimation and Inference in Economics. Oxford University Press. UK.

[3] Greene, W.H. 2002. Econometric Analysis (5thed). Prentice Hall.

[4] Iriany, A., Suhariningsih, Ruchjana, B.N., and Setiawan. 2013. Prediction of Precipitation Data at Batu Town using The GSTAR(1,p)-SUR. Journal of Basic and Applied Scientific Research.3(6): vol 3 no 6.

[5] Nainggolan, Nelson. 2012. Development of GSTAR Model with Assumption ARCH and its Application to Inflation. Dissertation Unpublihed. Bandung: ITB.

[6] Pfeifer, P.E and Deutsch, S.J. 1980a. Stationarity and Invertibility Regions for Low Order STARMA Models. Communications in Statistics-Simulation and Computation 9 (5). P. 551-562.

[7] Pfeifer, P.E and Deutsch, S.J.. 1980b. Identification and Interpretation of First Orde Space-Time ARMA Models.Technometrics, 22 (1), 397-408.
[8] Ruchjana, B.N. 2001. Study on the Weight Matrix in the Space-Time Autoregressive Model. Proceeding of the Tenth International Symposium on Applied Stochastic Models and Data Analysis (ASMDA). Gerard Govaert, et al. Editor. Universite de Technologie Compiegne. Prancis. Vol. 2/2. p. 789-794.
[9] Ruchjana, B.N. . 2002.A Generalized Space Time Autoregressive Model and its Application to Oil Production Data. Dissertation Unpublihed. Bandung : ITB.
[10] Suhartono dan Atok, R.M. 2006. Pemilihan Bobot Lokasi yang Optimal pada Model GSTAR. Prosiding Konferensi Nasional Matematika XIII, Universitas Negeri Semarang.
[11] Suhartono and Subanar. 2006. The Optimal Determination of Space Weight in GSTAR Model by Using Cross-sorrelation Inference Journal of Quantitative Methods: Journal Devoted the Mathematical and Statistical Application in Various Field.
[12] Setiawan. 1992. Study on Seemingly Unrelated Regression (SUR) and its application to Almost Ideal Demand System (AIDS). Thesis Unpublished. Bogor : IPB.
[13] Srivastava, V.K. and Giles, D.E.A. (1987). Seemingly unrelated regression equations models: estimation and inference. New York: Marcel Dekker. ISBN 978-0-82-477610-7.
[14] Wutsqa, D.U dan Suhartono. 2010. Peramalan Deret Waktu Multivariat Seasonal pada Data Pariwisata dengan VAR-GSTAR. Jurnal Ilmu Dasar Vol. II no. 1.
[15] Zellner, A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests for aggregation bias. Journal of the American Statistical Association 57: 348–368.