IOP Conference Series: Earth and Environmental Science

The 3rd International Conference on Life and Applied Sciences *for Sustainable Rural Development* (ICLAS-SURE) http://iclas.conference.unsoed.ac.id/

To cite this article: 2021 *IOP Conf. Ser.: Earth Environ. Sci.* **746** 011001

IOP Conf. Series: Earth and Environmental Science **746** (2021) 011001 doi:10.1088/1755-1315/746/1/011001

PREFACE

International Conference on Life and Applied Sciences for Sustainable Rural Development (ICLAS-SURE) is an annual international event organized by Institute of Research and Community Service, Universitas Jenderal Soedirman (Unsoed), Indonesia. Universitas Jenderal Soedirman (Unsoed) is one of the outstanding National University in Indonesa, which is located in Purwokerto, Central Java, Indonesia. This university was established by Minister of Higher Education and Science, Republic Indonesia, based on Presidential Decree No. 195 dated September 23, 1963. Since 1963, Universitas Jenderal Soedirman has been experiencing on rural resource development as well as community services.

Following the success of the **1st** and **2nd ICLAS-SURE, this year, the Institute of Research and Community Service, Universitas Jenderal Soedirman,** organize **The 3rd ICLAS-SURE. T**he vision of Jenderal Soedirman University is to be **globally recognized as a university that focuses on sustainable rural and local wisdom development**. Hopefully, this core competence in sustainable rural development shall initiate the university to be nationally and internationally renowned as the center of rural community empowerment. To achieve this vision and cope with the COVID 19 pandemic, this year, we bring the particular theme, "Interdisciplinary approaches and applied technologies for sustainable rural-environmental resources based on local wisdom before and during COVID-19 pandemic". COVID-19 has led to a significant loss of output, employment, and income, affecting rural development. To develop a sustainable rural development, we must fulfil three basic needs, i.e. people welfare improvement, protection of natural, landscape, and cultural resources, and food security through a sustainable farming production.

IOP Conf. Series: Earth and Environmental Science **746** (2021) 011001 doi:10.1088/1755-1315/746/1/011001

COMMITTEE

PAPER • **OPEN ACCESS**

Peer Review Declaration

To cite this article: 2021 *IOP Conf. Ser.: Earth Environ. Sci.* **746** 011002

IOP Conf. Series: Earth and Environmental Science **746** (2021) 011002 doi:10.1088/1755-1315/746/1/011002

PEER REVIEW DECLARATION

All papers published in this volume of IOP Conference Series: Earth and Environmental Science have been peer reviewed through processes administered by the Editors. Reviews were conducted by expert referees to the professional and scientific standards expected of a proceedings journal published by IOP Publishing.

The ICLAS-SURE committee is committed to maintaining the highest level of integrity in the content published paper in The 3rd ICLAS-SURE. All the papers we received have been peer-reviewed. There are two steps of the review process we conducted

1. **Preliminary Review**

   All papers submitted to ICLAS-SURE must fit the scope of The 3rd ICLAS-SURE. The scope was cehecked by the Editorial board. Then all of the papers had undergone a plagiarism check, English grammar check, and double-blind review by two reviewers. Based on the reviewer comments and the result of plagiarism and grammar check, we decided the paper which can be processed to the next step

   - **Type of peer review:** Double-blind, author and reviewer identities are hidden to each other
   - **Scope:** Biosciences**,** Agriculture, Engineering and applied sciences for rural development.
   - **Plagiarism and grammar checking:** Turnitin & Grammarly
   - **Conference submission management system:** Open Conference Systems (OCS).

2. **Content review**

   The papers passed the first review were reviewed to the next step, review by Scientific Committee and reviewers. The from the following aspects: Originality, Methodology, Novelty and Scientific Structure.

   - Type of peer review: Double-blind by Scientific Committee and reviewers
   - Number of abstract presented : 182 titles
   - Number of submissions paper sent for review : 113 papers
   - Number of submissions accepted: 45 papers
   - Acceptance Rate (Number of Submissions Accepted / Number of Submissions Received X 100): 39,8 %
   - Average number of reviews per paper: 2 round
   - Total number of reviewers involved: 22 reviewers

Contact person for queries:
Eko Murdyantoro AM
Jenderal Soedirman University, Jawa Tengah, Indonesia
Email : icmasure.lppm@unsoed.ac.id

KELENGKAPAN DAFTAR ISI

IOP Conference Series: Earth and Environmental Science

Table of contents

Volume 746

2021

Previous issue Next issue

3rd International Conference on Life and Applied Sciences for Sustainable Rural Development (ICLAS-SURE 2020) November 18-19, 2020 Central Java, Indonesia

Accepted papers received: 09 April 2021

Published online: 13 May 2021

Open all abstracts

Biosciences for Rural Development

Engineering & Applied Sciences for Rural Development

IOP Conference Series: Earth and Environmental Science

PAPER • **OPEN ACCESS**

Forecasting the amount of rainfall in West Kalimantan using Generalized Space-time Autoregressive model

To cite this article: R Utami *et al* 2021 *IOP Conf. Ser.: Earth Environ. Sci.* **746** 012035

IOP Conf. Series: Earth and Environmental Science **746** (2021) 012035 doi:10.1088/1755-1315/746/1/012035

Forecasting the amount of rainfall in West Kalimantan using Generalized Space-time Autoregressive model

R Utami*, N Nurhayati, S Maryani

Department of Mathematics, Faculty of Mathematics and Natural Sciences, Jenderal Soedirman University

*E-mail: riani.utami@mhs.unsoed.ac.id

Abstract. The generalized space-time autoregressive or GSTAR is a space-time model which can be used to analyze time-series data in several locations considered to be correlated. In this research, the GSTAR model is applied to forecast the amount of rainfall in West Kalimantan, especially at Sintang Station, Melawi Station, and Ketapang Station. The data used for modeling is data of the amount of rainfall for the period January 2013-December 2017, while the data used for model validation is data for the period January 2018-December 2018. The spatial weights used are uniform weights, inverse distance weights, and normalized cross-correlation weights, and the estimation method used is the ordinary least square or OLS estimation. The best model is selected based on the smallest RMSE (root mean square error). The results showed that all spatial weights gave the same good GSTAR(1:1) model because they had almost the same RMSE value. Thus, this model can be used to forecast the amount of rainfall for the period January 2019-December 2019. The forecast results show that for Sintang Station and Melawi Station, the highest amount of rainfall is estimated to occur in March 2019 and the lowest will occur in August 2019. Meanwhile, for Ketapang Station, the highest amount of rainfall is estimated to occur in January 2019 and the lowest will occur in September 2019.

1. Introduction

Rain is part of the water cycle and is the main water source that supplies water to the earth's surface. The volume of rain that occurs at a certain time is called the amount of rainfall. The amount of rainfall in an area is usually influenced by the amount of rainfall in other areas. This makes the amount of rainfall in a location with other nearby locations tend to have almost the same amount of rainfall. Apart from being influenced by other regions, rainfall is also influenced by previous times. Therefore, rainfall data are considered as spatio-temporal data.

The amount of rainfall at a location can be predicted using a space-time model, one of which is the Generalized Space-time Autoregressive (GSTAR) model. The GSTAR model was chosen because this model can be used to predict a spatial phenomenon or the phenomenon of the occurrence of an area that is influenced by the events of other regions. The GSTAR model is a generalization of the Space-Time Autoregressive (STAR) model. In the STAR model, the parameters are assumed to be the same for all locations, while GSTAR is assumed to be different. Therefore, the GSTAR model is considered more realistic than the STAR model [1]. In the GSTAR model, the spatial relationship is represented by the spatial weight matrix $\boldsymbol{W} = (w_{ij})$ measuring $N \times N$, with w_{ij} representing the spatial relationship between location i and location j [1].

The GSTAR model with time order p and spatial order $\lambda_1, \lambda_2, \dots, \lambda_p$ denoted $(p: \lambda_1, \lambda_2, \dots, \lambda_p)$ can be written as follows.

$$\mathbf{z}(t) = \sum_{k=1}^{p}\left[\boldsymbol{\Phi}_{k0} + \sum_{\ell=1}^{\lambda k} \boldsymbol{\Phi}_{k\ell}\boldsymbol{W}^{(\ell)}\right] \mathbf{z}(t-k) + \boldsymbol{\varepsilon}(t), \tag{1}$$

where $\mathbf{z}(t) = [z_1(t), z_2(t), \dots, z_N(t)]$ for $\mathbf{z}(t) = [z_1(t), z_2(t), \dots, z_N(t)]$ is the observation vector with dimension N at time t. Furthermore, $\boldsymbol{\Phi}_{k0} = \text{diag}\,(\emptyset_{k0}^{(1)}, \dots, \emptyset_{k0}^{(N)}$ is a diagonal matrix with the element $\emptyset_{k0}^{(i)}$ denotes the autoregressive parameter at lag time k in location i, and $\boldsymbol{\Phi}_{k\ell} = \text{diag}\,(\emptyset_{k\ell}^{(1)}, \dots, \emptyset_{k\ell}^{(N)})$ is a diagonal matrix with $\emptyset_{k\ell}^{(i)}$ denotes the space-time parameter at lag time k and spatial order ℓ in location i. Meanwhile, $\boldsymbol{W}^{(\ell)}$ is a spatial weight matrix of order ℓ with the elements $0 \leq w_{ij} \leq 1$ and $\sum_{i \neq j} w_{ij} = 1$, $\boldsymbol{\varepsilon}(t) = (\varepsilon_1(t), \varepsilon_2(t), \dots, \varepsilon_N(t))$ is the error vector with N dimension at time t with $\varepsilon_i(t)$ represents the model error at location i at time t which is following the white noise assumption (constant mean and variance, and uncorrelated) and normally distributed.

Research about GSTAR has been applied in various fields, such as GDP data modeling in West European Countries [2], and forecasting oil production data at Volcanic Layer Jatibarang, West Java, Indonesia [3]. Motivated by this result, this research will focus on forecasting the amount of rainfall in West Kalimantan using the GSTAR model using three spatial weights, uniform weight, inverse distance weight, and normalized cross-correlation weight. In 2017, [4] also predicted the amount of rainfall in West Kalimantan but different in location and the type of spatial weights.

2. Method

The data used in this research is rainfall data at three stations in West Kalimantan, that is Sintang Station, Melawi Station, and Ketapang Station. Data obtained from Badan Pusat Statistik (BPS), West Kalimantan Province from January 2013 to December 2018. The variables used in this research are presented in Table 1.

Table 1. Research variables

Variable	Description	Unit
$z_1(t)$	The amount of rainfall at Sintang Station at time t after is subtracted by the average value	millimeter
$z_2(t)$	The amount of rainfall at Melawi Station at time t after is subtracted by the average value	millimeter
$z_3(t)$	The amount of rainfall at Ketapang Station at time t after is subtracted by the average value	millimeter

To analyze the data, we use free statistical software, R-4.0.3. The procedure of this research is

1. Describe the data.
2. Divide the data into two groups, namely:
   a. In-sample data: January 2013 - December 2017 (60 observations)
   b. Out-sample data: January 2018 - December 2018 (12 observations)
3. Check the data stationarity
4. Determine the weight matrix in the GSTAR model, namely uniform weight, inverse distance weight, normalized cross-correlation weight.
5. Choose the GSTAR model's order by looking at the ACF plot and the PACF plot.
6. Estimate model parameters using the OLS (ordinary least square) method.
7. Check residual assumptions.

8. Calculate the RMSE value for each model.
9. Select the model based on the smallest RMSE value.
10. Forecast the amount of rainfall in the next period,

3. Result and Discussion

This section discusses the research results included data description, stationarity testing, spatial weight matrix, GSTAR model identification, parameter estimation, checking the residual assumptions, calculating the RMSE value, and forecasting the amount of rainfall in the next period.

3.1. Data Description

The statistics of the rainfall data at three stations in Kalimantan Barat are presented in Table 2. From the table, we found that Melawi Station has the highest average rainfall, while Sintang Station has the lowest average rainfall. The range between the minimum and maximum values is quite large. Comparing to other stations, the standard deviation in Melawi is also quite large. It shows that data distribution occurred in Melawi Station is spread widely.

Table 2. Descriptive statistics of rainfall data in West Kalimantan (in millimeter)

Statistic	Sintang Station	Melawi Station	Ketapang Station
Average	255.83	324.60	231.50
Standard Deviation	121.99	145.45	141.29
Minimum	26.40	61.00	19.50
Maximum	633.50	715.80	556.00

3.2 Stationarity Test

Data is stationary if the mean and variance are constant [5]. Data is "stationary in the mean" if the data is stable fluctuating around the average. Data is "stationary in the variance" if the data fluctuates from time to time, but the average does not need to be constant. The stationarity can be checked by examining the time series data plot and ADF test. The data plot can be seen in Figure 1.

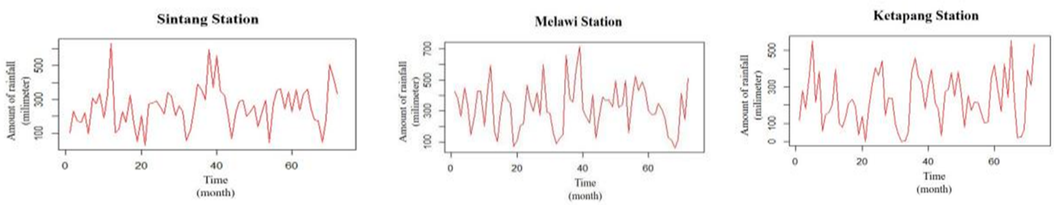

Figure 1. Plot of the rainfall data at Sintang Station, Melawi Station, and Ketapang Station.

Figure 1 shows that the fluctuation of the plot is around the average value and the fluctuation is stable, it can be concluded that the rainfall data at three locations are stationary in the mean and variance.

Stationary identification by looking only at a plot of the data pattern is often subjective. Alternatively, data stationarity can be identified using the ADF test. The ADF test was carried out using tseries package on the R-4.0.3 software. The ADF test results are shown in Table 3. Table 3 shows that each variable has a p-value <0.05, so it can be concluded that the data is stationary in the mean and variance.

Table 3. ADF test

No	Variable	p-value	Decision
1.	$z_1(t)$	0.040	Stationery
2.	$z_2(t)$	0.010	Stationery
3.	$z_3(t)$	0.010	Stationery

3.3 Spatial Weight Matrix
The weight matrix of the GSTAR model used in this research is the uniform weight matrix, the inverse distance weight matrix, and the normalized cross-correlation weight matrix.

3.3.1. Uniform weight matrix. The element of a uniform weight matrix in the GSTAR model is calculated based on the number of nearby locations. According to [6], uniform weight is calculated by the formula

$$w_{ij} = \frac{1}{n_i} \tag{2}$$

where n_i is the number of the nearby location to i location in the first-order spatial lag.

Table 4. Location and the nearby location

Location	Nearby location	Number of the nearby location
Sintang	Melawi	1
Melawi	Sintang and Ketapang	2
Ketapang	Melawi	1

From Table 4 and equation (2), we obtain the following uniform weight matrix

$$\boldsymbol{W} = \begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0 & 0.5 \\ 0 & 1 & 0 \end{bmatrix}.$$

3.3.2. Inverse distance matrix. The element of an inverse distance weight matrix is calculated based on the actual distance. The formula is

$$w_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j=1}^{N} \frac{1}{d_{ij}}}, \quad j \neq i \tag{3}$$

and $w_{ij} = 0$ for $j = i$. In equation (3), d_{ij} is the distance from location i to location j [7].

Table 5. Distance between rain stations

No	Label	Definition	Value
1.	d_{AB}	the distance from Sintang Station to Melawi Station	72 km
2.	d_{AC}	the distance from Sintang Station to Ketapang Station	573 km
3.	d_{BC}	the distance from Melawi Station to Ketapang Station	621 km

From Table 5 and equation (3), we get the following inverse distance weight matrix

$$\boldsymbol{W} = \begin{bmatrix} 0 & 0.888 & 0.112 \\ 0.896 & 0 & 0.104 \\ 0.520 & 0.480 & 0 \end{bmatrix}.$$

3.3.3. Normalized cross-correlation weight matrix. The element of a cross-correlation weight matrix between two locations is calculated for each time lag k. According to [8], the normalized cross-correlation weight is calculated by the formula (4).

$$w_{ij} = \frac{r_{ij}(k)}{\sum_{K \neq i} |r_{iK}(k)|} \tag{4}$$

where

$$r_{ij}(k) = \frac{\sum_{t=k+1}^{T}\left[(z_i(t) - \bar{z}_i)(z_j(t-k) - \bar{z}_j)\right]}{\sqrt{\sum_{t=1}^{T}(z_i(t) - \bar{z}_i)^2 \sum_{t=1}^{T}(z_j(t) - \bar{z}_j)^2}}$$

is the cross-correlation between location i and j. The cross-correlation value for the first lag time is presented in Table 6.

Table 6. Cross correlation values for k = 1

$r_{ij}(k)$	Description	$k = 1$
$r_{AB}(k)$	Cross correlation value between Sintang Station and Melawi Station	0.236
$r_{AC}(k)$	Cross correlation value between Sintang Station and Ketapang Station	0.140
$r_{BA}(k)$	Cross correlation value between Melawi Station and Sintang Station	0.316
$r_{BC}(k)$	Cross correlation value between Melawi Station and Ketapang Station	0.107
$r_{CA}(k)$	Cross correlation value between Ketapang Station and Sintang Station	0.235
$r_{CB}(k)$	Cross correlation value between Ketapang Station and Melawi Station	0.244

From equation (4) and Table 6, we get the normalized cross-correlation weight as follows

$$\boldsymbol{W} = \begin{bmatrix} 0 & 0.628 & 0.372 \\ 0.747 & 0 & 0.253 \\ 0.491 & 0.509 & 0 \end{bmatrix}.$$

3.4 Model Identification

The order of the GSTAR model can be identified based on the ACF plot and the PACF plot for each location. ACF plot and PACF plot can be seen in Figure 2 and Figure 3.

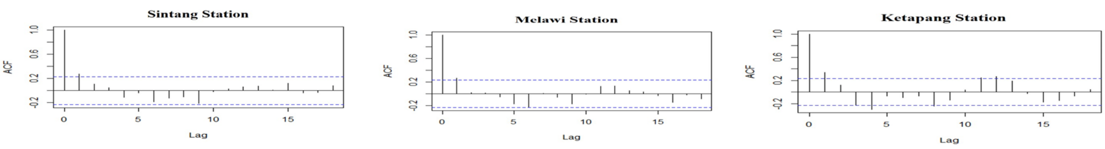

Figure 2. ACF plot for $z_1(t)$, $z_2(t)$, and $z_3(t)$.

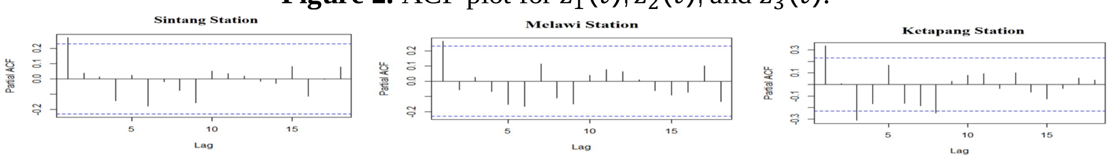

Figure 3. PACF plot for $z_1(t)$, $z_2(t)$, and $z_3(t)$.

Based on Figure 2 and Figure 3, it can be seen that the ACF plot and the PACF plot cut off at the first lag so that the possible order of the GSTAR model is only the GSTAR(1:1) model.

3.5 Model Estimation

The OLS method is the best estimation method that is unbiased, linear, and the best (BLUE). According to [1], GSTAR model for each location *i* can be written as

$$\boldsymbol{z}_i = \mathbf{X}_i\boldsymbol{\phi}_i + \boldsymbol{\varepsilon}_i \quad (5)$$

where,

$$\boldsymbol{z}_i = \begin{bmatrix} z_i(p) \\ z_i(p+1) \\ \vdots \\ z_i(T) \end{bmatrix}, \ \mathbf{X}_i = \begin{bmatrix} v_i^{(0)}(p-1) & \cdots & v_i^{(\lambda_1)}(p-1) & \cdots & v_i^{(0)}(0) & \cdots & v_i^{(\lambda_p)}(0) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ v_i^{(0)}(T-1) & \cdots & v_i^{(\lambda_1)}(T-1) & \dots & v_i^{(0)}(T-p) & \cdots & v_i^{(\lambda_p)}(T-p) \end{bmatrix},$$

$\boldsymbol{\phi}_i{}' = (\phi_{10}^{(i)}, \cdots, \phi_{1\lambda_1}^{(i)}, \phi_{20}^{(i)}, \cdots, \phi_{2\lambda_2}^{(i)}, \cdots, \phi_{p0}^{(i)}, \cdots \phi_{p\lambda_p}^{(i)})$, and $\boldsymbol{\varepsilon_i} = \begin{bmatrix} \varepsilon_i(p) \\ \varepsilon_i(p+1) \\ \vdots \\ \varepsilon_i(T) \end{bmatrix}$.

Therefore, the GSTAR model for all locations can be presented as the following linear model

$$\boldsymbol{z} = \boldsymbol{X\phi} + \boldsymbol{\varepsilon}, \quad (6)$$

where $\boldsymbol{z} = (z_1', \dots, z_N')'$, $\boldsymbol{X} = \text{diag}(X_1, \dots, X_N)$, $\boldsymbol{\phi} = (\phi_1', \dots, \phi_N')$, and $\boldsymbol{\varepsilon} = (\varepsilon_1', \dots \varepsilon_N')$.

Estimation of parameters using the OLS method can be obtained by minimizing the number of squares of errors defined as

$$\boldsymbol{X'X\phi} = \boldsymbol{X'z} \quad (7)$$

The estimation results of the GSTAR model parameters using uniform weights, inverse distance weights, and normalized cross-correlation weights can be seen in Table 7.

Table 7. GSTAR(1;1) parameter estimates for each spatial weight

Parameter	Uniform weight	Inversion distance weight	Normalized cross-correlation weight
$\phi_{10}^{(1)}$	0.306	0.299	0.292
$\phi_{10}^{(2)}$	0.235	0.205	0.206
$\phi_{10}^{(3)}$	0.522	0.544	0.542
$\phi_{11}^{(1)}$	0.098	0.111	0.127
$\phi_{11}^{(2)}$	0.245	0.289	0.294
$\phi_{11}^{(3)}$	0.089	0.043	0.048

Based on equation 1, the GSTAR model equation for each location can be calculated by substituting the estimated value in Table 7 to the matrix $\boldsymbol{\Phi}_{k0}$ and matrix $\boldsymbol{\Phi}_{k\ell}$. The GSTAR model equation for each location can be written as follows

1. GSTAR(1:1) for uniform weight

$$z_1(t) = [0.306\, z_1(t-1) + 0.098\, z_2(t-1)] + \varepsilon_1(t),$$
$$z_2(t) = [0.235\, z_2(t-1) + 0.123\, z_1(t-1) + 0.122\, z_3(t-1)] + \varepsilon_2(t),$$
$$z_3(t) = [0.522\, z_3(t-1) + 0.089\, z_2(t-1)] + \varepsilon_3(t).$$

2. GSTAR(1:1) model for inverse distance weight

$$z_1(t) = [0.299\, z_1(t-1) + 0.098\, z_2(t-1) + 0.012\, z_3(t-1)] + \varepsilon_1(t),$$
$$z_2(t) = [0.205\, z_2(t-1) + 0.259\, z_1(t-1) + 0.030\, z_3(t-1)] + \varepsilon_2(t),$$
$$z_3(t) = [0.544\, z_3(t-1) + 0.022\, z_1(t-1) + 0.021\, z_2(t-1)] + \varepsilon_3(t).$$

3. GSTAR(1:1) model for normalized cross-correlation weight

$$z_1(t) = [0.292\, z_1(t-1) + 0.079\, z_2(t-1) + 0.047\, z_3(t-1)] + \varepsilon_1(t),$$
$$z_2(t) = [0.206\, z_2(t-1) + 0.219\, z_1(t-1) + 0.074\, z_3(t-1)] + \varepsilon_2(t),$$
$$z_3(t) = [0.542\, z_3(t-1) + 0.024\, z_1(t-1) + 0.024\, z_2(t-1)] + \varepsilon_3(t).$$

The GSTAR model equation with a negative coefficient interprets that the amount of rainfall in an area in the previous negatively affected the amount of rainfall in the current period. Conversely, a positive coefficient value shows that the amount of rainfall in an area in the previous period has a positive effect on the amount of rainfall in the current period. For example, the GSTAR(1:1) model with uniform weight at Ketapang Station can be interpreted, if the amount of rainfall last month at Ketapang Station increased by 1 mm, while at other stations and other times it was constant, the rainfall at the Ketapang Station in the next period will decrease by 0.522 mm.

3.6 Checking Model Assumption

The model assumptions in this research are white noise assumption and normality assumption. White noise assumption can be inferred from the stationary residual around zero, and plot of residuals ACF and residuals PACF which lied on their confidence interval line. Normality assumption can be deduced from the symmetric histogram linear Q-Q plot of residuals. The results of checking GSTAR(1:1) model assumption for each spatial weight is presented in Table 8.

Table 8. Results of GSTAR(1:1) model assumption for each spatial weight.

No	GSTAR model	White noise assumption	Normality assumption
1.	Uniform weight	The assumption is fulfilled	The assumption is fulfilled
2.	Inverse distance weight	The assumption is fulfilled	The assumption is fulfilled
3.	Normalized cross-correlation weight	The assumption is fulfilled	The assumption is fulfilled

Table 8 shows that GSTAR(1:1) model assumption for each spatial weight matrix has been fulfilled. It means that the model is suitable to forecast the amount of rainfall in West Kalimantan.

3.7 Calculation of RMSE Value

The criterion for selecting the best model is determined by the RMSE value. The best model has the smallest RMSE value. The RMSE value can be calculated by the following formula

$$RMSE = \sqrt{\left(\frac{1}{T}\sum_{t=1}^{T}(z_t - \hat{z}_t)^2\right)} \quad (8)$$

where z_t is the observed value at time t, and $\hat{z}_t$ is the predicted value at time t. The criteria for selecting the best model are determined by taking into account the RMSE value based on the in-sample residual. The results of forecasting accuracy can be known based on the value based on the out-sample residual. The best model is the model that has the smallest RMSE value.

Table 9. RMSE value in the GSTAR(1:1) model for each spatial weight.

Spatial weight matrix	in-sample RMSE			Average	out-sample RMSE			Average
	$z_1(t)$	$z_2(t)$	$z_3(t)$		$z_1(t)$	$z_2(t)$	$z_3(t)$	
Uniform	115.32	139.51	121.10	125.31	114.63	132.78	180.21	142.54
Inversion distance	115.33	137.99	121.76	125.02	114.66	128.98	180.23	141.29
Normalized cross-correlation	115.51	138.36	121.73	125.20	114.57	130.98	180.09	141.88

Table 9 shows that the in-sample RMSE and the out-sample RMSE for each spatial weight gave almost the same RMSE value. This proves that all the models produced are equally good, so that in predicting the amount of rainfall in the next period it is carried out using the GSTAR(1:1) model with three spatial weights, namely uniform weights, inverse distance weight, and normalized cross-correlation weight.

3.8 Forecasting The Next Period

A good forecast is a forecast that produces a forecast value that is not far from the true value. Forecasting the amount of rainfall in the next period is obtained from the GSTAR(1:1) model with three spatial weights there are uniform weight, inverse distance weight, and normalized cross-correlation weight. Forecasting the amount of rainfall for the next periods is presented in Table 10.

Based on Table 10, it can be seen that the results of forecasting the amount of rainfall in January 2019 to December 2019 for Sintang Station, Melawi Station, and Ketapang Station are fluctuating results. The forecast results for Sintang Station and Melawi Station, the highest amount of rainfall is estimated to occur in March 2019 and the lowest will occur in August 2019. As for Ketapang Station, The highest amount of rainfall is estimated to occur in January 2019 and the lowest will occur in September 2019.

Table 10. Forecasting the amount of rainfall for the next 12 months for each spatial weight

Time	Uniform weight			Inverse distance weight			Normalized cross-correlation		
	Sintang Station	Melawi Station	Ketapang Station	Sintang Station	Melawi Station	Ketapang Station	Sintang Station	Melawi Station	Ketapang Station
30-Jan-19	296.11	414.07	406.41	299.41	390.39	402.08	305.84	401.07	402.16
28-Feb-19	255.36	320.87	245.98	255.70	320.40	249.71	257.58	321.44	249.51
30-Mar-19	315.17	412.85	353.39	316.79	405.80	346.60	318.81	409.67	347.09
30-Apr-19	310.85	342.29	204.06	308.93	370.85	205.98	305.60	361.49	206.46
30-May-19	295.32	364.75	361.26	297.48	361.39	372.42	305.98	367.00	371.97
30-Jun-19	196.38	268.40	157.32	195.96	260.08	156.64	194.35	260.99	156.33
30-Jul-19	229.49	301.71	254.12	230.59	291.87	261.16	235.00	296.56	260.58
30-Aug-19	178.01	230.08	116.19	176.97	227.90	122.10	175.86	226.97	121.46
30-Sep-19	196.11	231.35	99.46	194.25	240.84	106.92	191.90	236.07	106.43
30-Oct-19	197.97	240.58	102.85	196.18	247.76	107.10	192.99	243.31	106.75
30-Nov-19	216.31	270.37	175.56	215.83	271.06	181.78	216.34	270.56	181.32
30-Dec-19	311.74	359.68	251.46	310.94	378.30	252.77	309.95	373.03	253.15

4. Conclusion

The GSTAR model suitable for rainfall forecasting in West Kalimantan is the GSTAR(1:1) model with uniform weight, inverse distance weight, or normalized cross-correlation weight. The forecast results show that for Sintang Station and Melawi Station, the highest amount of rainfall is estimated to occur in March 2019 and the lowest will occur in August 2019. As for Ketapang Station, the highest amount of rainfall is estimated to occur in January 2019 and the lowest will occur in September 2019.

Acknowledgment

The research is funded by the Directorate of Research and Community Service (DRPM) Deputy of Research and Development Strengthening, Kemenristek-BRIN Indonesia, according to Research Contract No. 176/SP2H/AMD/LT/DRPM/2020.

References

[1] Borovkova S, Ruchjana B N, and Lopuhaa H 2008 Consistency and Asymptotic Normality of Least Squares Estimators in Generalized Space-time Models *Stat. Neerl.* **62**(4) 482-508.

[2] Nurhayati N, Pasaribu U S, and Neswan O 2012 Application of Generalized Space-Time Autoregressive Model on GDP Data in West European Countries *J. Probab. Stat.* **2012** 1-16.

[3] Ruchjana B N, Borovkova S A, and Lopuhaa H P 2012 Least Squares Estimation of Generalized Space-Time Autoregressive (GSTAR) Model and Its Properties *The 5th International Conference on Research and Education in Mathematics,* American Institute of Physics pp. 61-64.

[4] Adam I, Kusnandar D, and Perdana H 2017 Application GSTAR(1,1) Model for Rainfall Data *Buletin Ilmiah Matematika, Statistik, dan Terapannya (Bimaster).* **6**(3) 159-166.

[5] Box G, Jenkins G M, Reinsel G, and Ljung G 2016 *Time Series Analysis: Forecasting and Control, fifth edition* (New Jersey).

[6] Yaffee R and McGee M 2000 *Time Series Analysis and Forecasting* (Academic Press, Inc. New York).

[7] Ruchjana B N 2002 Generalized Space-Time Autoregressive Model and Its Application to Oil Production *Forum Statistika dan Komputasi* (Bogor: IPB).

[8] Anggraeni D, Prahutama A, and Andari S 2013 Application of Generalized Space-time Autoregressive (GSTAR) for Volume of Vehicles Entering The Semarang Toll Road *Media Statistika* **6**(2) 71-80.