Rainfall model on area of rice production in Sragen, Karanganyar and Klaten by using Generalized Space Time Autoregressive (GSTAR)

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ABSTRACT. The planning of planting period became non-optimal due to the uncertain rainfall fluctuation condition in the past few years. To anticipate food insecurity caused by such a matter, the development of rainfall prediction models in several rice production areas in Central Java, which represent the center for rice production, is required. This paper provides the application of GSTAR model on the rainfall data in Sragen Regency, Karanganyar Regency, and Klaten Regency with considering time and location conditions. The weighting applied in the model was normalized cross-correlation. By applying the least square method and stepwise procedure, GSTAR model for six, seven in Sragen, seven areas in Karanganyar, and seven areas in Klaten respectively was obtained. The validity of the model was tested by applying RMSE.

1. Introduction

One of the important roles of Central Java Province for the regional and national economy is as the food barn. One of staple food resources of the majority of Indonesian communities is rice, making it as the superior food staple commodity in Indonesia and one of the government’s main concerns in maintaining the national food security and stability. The availability and access to the commodity and its production continuity highly affect the national food security.

The rice production in Central Java has a surplus, which makes it potential to support the regional food security. Nationally, it was the biggest rice producer with the production of 10.34 million tons of unhulled rice in 2014. By the paddy-into-rice conversion factor assumption with the number of 62.74% and the level of per capita rice consumption of 139.15 kg per year, Central Java is therefore, potential to have the surplus of 1.86 million tons of rice. It is considered significant to support the national rice surplus target which aims for 10 million tons of rice per year. In accordance with the high production capacity, the rice productivity in Central Java is 56.06 quintal per hectare, which is higher than its national average. Considering its important role, the food production in Central Java needs to be maintained by establishing an appropriate cropping pattern.
Rice cropping pattern can be determined through climate and location factors. The global warming has caused climate changes such as temperature increment, sea water level increment and rainfall pattern shifting. *El Niño* and *La Niña* are the extreme climate conditions with a long duration, and they are allegedly affected by global warming, which seriously affects the agricultural productions [4]. *El Niño* is condition when the Equatorial Pacific surface temperatures become warm, especially around the eastern part [3]. *El Niño* causes the eastern Equatorial Pacific surface warm, followed by rainfall increment around Pacific areas and rainfall degradation in the areas of Southeast Asia and Australia. On the contrary, *La Niña* causes western Pacific surface warm and higher rainfalls in the areas of Southeast Asia and Australia. Due to the temperature increment and the frequent *El Niño*, rice production in most of Asian countries experienced degradation in the past few years ([2], [11]). *La Niña* also causes disadvantages such as floods and the increment of plant pest organism due to above-normal rainfalls and humidity level increment. *El Niño* and *La Niña* occur irregularly that both of them can shift the time period of rainy season and dry season and also causes changes on food commodity cropping pattern for the farmers.

The planning of planting period became non-optimal due to the uncertain rainfall fluctuation condition in the past few years. To respond food insecurity caused such a condition, the development of the rainfall prediction model in food production areas which represent the centers of food production, especially rice, is required.

Research on rice plants was initiated by [15] and [16] by modeling a robust regression which used M-estimation, S-estimation, and MM-estimation parameter and spacial modelling. In 2015, a new regression model was developed using Geographically Weighted Regression (GWR). This model considered geographical condition and was constructed for corn production in every area in Central Java [14]. A spatial model was also developed in the same year which applied spatial weights (location) in modeling the rice production in Indonesia [15].

The research above will be developed in one of the factors that affect rice production, namely rainfall. Fluctuation in rainfall really affects the result of rice production. The rainfall pattern model, in the form of time series data, needs to be constructed in some rice production centers in Central Java. Some statistical methods used to predict the rainfall were Autoregressive Integrated Moving Average (ARIMA), Wavelet transformation, and Adaptive Neuro-Fuzzy Inference System (ANFIS). Those methods were only based on time in the past and did not consider geographical factor. Thus, there is a need to develop a method to increase the accuracy of rainfall prediction.

Model which considers location and time factors is known as Space Time Autoregressive (STAR) or Generalized Space Time Autoregressive (GSTAR). The STAR model is time and location model, which was firstly introduced by Pfeifer and Deutsch [5]. In this model, the space parameters in all area are considered the same (homogenous). Meanwhile the rainfall data in some centers of rice production area in Central Java are possibly heterogeneous. Ruchjana [6] developed the STAR method into GSTAR, which perfects the STAR through the use of different space parameter for each area. This is in accordance with the heterogeneous state in the field. Therefore, the GSTAR is more suitable method to be used to predict the rainfall in Central Java even for the smallest level of prediction that is rainfall station. According to [6], the model needs stationary data. Some sampled areas in this model considered condition of location and linkage between locations so that the appropriate weighting factor is included in the model.

Suhartono and Subanar [10] suggest various methods to decide the location weighting in the GSTAR model, namely: uniform weighting, binary weighting, distance inversion, and normalized cross correlation weighting. Uniform weighting was not compatible to be used in the GSTAR model because the location characteristic was heterogeneous. The binary weighting was also not compatible to be used in GSTAR model. This weighting was subjective because a closer location was scored 1 while a further location was scored 0. Location Correlation was also not compatible based on the location approach. The normalized cross correlation weighting was required to be used in GSTAR model because it considered the correlation of the data which have space and time effects.

The GSTAR model in literatures mentioned above was developed with weighted normalized cross correlation to model the rainfall in the regencies of Sragen, Karanganyar, and Klaten of Central Java which are the centers of rice production.
2. Research Method
In Central Java, the regencies of Sragen, Karanganyar, and Klaten are the rice production centers which fulfill the food need of the society of surrounding and outside the areas. For GSTAR rainfall modeling, the researchers took the monthly rainfall data of the years of 2009-2014 from six rice production areas in Sragen Regency: Masaran, Ngrampal, Tanon, Karang Malang, Plupuh, Kedawung; of the years of 1995-2014 from seven rice production areas in Karanganyar Regency: Kebak Keramat, Jaten, Karanganyar, Mojogedang, Karangpandan, Matesih, Tasik Madu; and of the years of 2010-2014 from seven rice production areas in Klaten Regency: Polanharjo, Cawas, Trucuk, Karangdowo, Wonasari, Delanggu, Juwiring.

The steps of the research were checking the data stationarity. Then, autoregressive order (p) in GSTAR model was determined by applying the model of VAR order p. The order determination was done by looking for the least value of AIC. Next, the weighted normalized cross-correlation was calculated based on the rainfall data. After that, a parameter prediction was done with the least square method, and its significance was tested according to autoregressive order (p) and spatial order (λs) for each weight of locations, and in this step, GSTAR model was formed. GSTAR model for each weight was then verified by applying root mean square error (RMSE) and then the normally distributed white noise residual was checked.

3. VAR Model
Vector autoregressive model (VAR) which is proposed by [8] in macroeconomics can be stated as
\[ Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t, \quad t = 1, \ldots, T \]
with \( Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt}) \) as the cascading time variable vector in time \( t(n \times 1) \), \( \varphi \) as the coefficient matrix \((n \times n)\) and \( \varepsilon_t \) as the white noise residual vector in \( t(n \times 1) \).

4. GSTAR Model
GSTAR model is a special form of VAR model which considers the spatial factor. The general model of GSTAR \((p, \lambda_s)\), (see [1] or [14]) can be stated as:
\[
\sum_{k=1}^{p} \sum_{l=0}^{\lambda_s} \sum_{i=1}^{n} \Phi_{kl} W^l(k) Z_{t,k} + \varepsilon_{lt}
\]
with \( \Phi_{kl} \) as spatial matrix diagonal with spatial lag \( l \) and time lag to \( k \) in area \( i \), \( W^l(k) \) as dimension weighting matrix \((n \times n)\), \( \varepsilon_{lt} \) as normalized residual \((n \times 1)\) in area \( i \) time \( t \), \( Z_{t,k} \) as the observation in area \( i \) time \( t \).

4.1. Model Stationarity Assumption
The forming of GSTAR model began with the data stationarity determination. According to [6], test statistic can be done through augmented Dickey Fuller (ADF) test with the following steps:
1. \( H_0 \): The data are not stationary
2. \( H_1 \): The data are stationary
3. Significance level determination
4. Critical area : \( H_0 \) is rejected when the value of \( ADF \) \( t \) < MacKinnon table \((\alpha; T - p)\)
4. Test Statistic :
\[
t = \frac{\sum_{t=1}^{n} Z_{t-1} Z_t - 1}{\sum_{t=1}^{n} Z_t^2}
\]
\[
\frac{\sum_{t=1}^{n} (Z_{t-\eta} Z_{t-1})^2}{\eta - 1}
\]
\( n \) as the number of data and \( p \) as the number of parameter.
4.2. Weighted Normalized Cross-Correlation

Weighted normalized cross-correlation is the location weightings using the result of normalized cross-correlation between locations in the consistent time lag. According to Wutsqa et al. [14] weighted normalized cross-correlation provides any possible correlations between locations. Weighted normalized cross-correlation can be stated as:

\[ w_{ij}(k) = \frac{r_{ij}(k)}{\sum_{k=1}^{p} |r_{ik}(k)|} \]

with \( i \neq j, k = 1,2,\ldots, p \), and the value of \( r_{ij}(k) \) as the cross-correlation which follows the following equation:

\[ r_{ij}(k) = \frac{\sum_{t=k+1}^{n} (Z_i(t) - \bar{Z}_i)(Z_j(t - k) - \bar{Z}_j)}{\sqrt{\sum_{t=1}^{n} (Z_i(t) - \bar{Z}_i)^2} \left( \sum_{t=1}^{n} (Z_j(t) - \bar{Z}_j)^2 \right)^{\frac{1}{2}}} \]

4.3. Model Identification

GSTAR model has a space and time correlation which is why its model orders are autoregressive order and spatial order. GSTAR model autoregressive order determination can be done with the order from VAR (p) model with the criterion of: the optimal lag length applies the least value of AIC ([14], [13]). According to Tsay [12], the value of AIC can be formulaized as:

\[ AIC = \ln \left( \frac{MSE}{n} \right) + \frac{2K^2}{n} \]

4.4. Model Parameter Estimation

Parameter estimation for GSTAR model can be done by applying the least square method. Based on the above model (2), it can be stated as:

\[ \begin{pmatrix} Z_1(1) \\ \vdots \\ Z_1(T) \\ \vdots \\ Z_n(1) \\ \vdots \\ Z_n(T) \end{pmatrix} = \begin{pmatrix} \phi_{k0}^1 Z_1(T-k) \\ \phi_{k0}^2 Z_2(T-k) \\ \phi_{k0}^3 Z_3(T-k) \\ \vdots \\ \phi_{k0}^6 Z_6(T-k) \\ \vdots \\ \phi_{k0}^n Z_n(T-k) \end{pmatrix} + \begin{pmatrix} \phi_{kl}^1 & 0 & 0 \\ 0 & \phi_{kl}^2 & 0 \\ 0 & 0 & \ddots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & \cdots & \phi_{kl}^n \end{pmatrix} \begin{pmatrix} e_1(T) \\ \vdots \\ e_2(T) \\ \vdots \\ e_3(T) \\ \vdots \\ e_n(T) \end{pmatrix} \]
with \( V_i(t) = \sum_{j=1}^{n} w_{ij}(k)Z_i(t) \)

The model for \( i \) location can be stated as:

\[
Z_i = Z_i^t \Phi + \epsilon
\]

so that the \( \Phi \) parameter estimation for each location can be calculated separately. First, formulating the least squares method of \( \epsilon = Z_i - Z_i^t \Phi \) has to be done in order to estimate the \( \Phi \) parameter and determining the RSS as follows:

\[
e' \epsilon = (Z - Z^t \Phi)'(Z - Z^t \Phi) = Z'Z - Z'Z^t \Phi - \Phi'Z^t Z + \Phi'Z^t Z^t \Phi
\]

By minimizing, the RSS \( \Phi \) parameter estimation was obtained as follows:

\[
\frac{\partial e' \epsilon}{\partial \Phi} = -2Z'^t Z + 2\Phi Z'^t Z^t = 0
\]

\[
\hat{\Phi} = (Z'^t Z)^{-1}Z'^t Z.
\]

4.5. Stepwise Regression

One way to determine a good regression model is by checking its parameter significance. Stepwise regression combines forward and backward method into bidirectional elimination. Stepwise regression method chooses the variable by the biggest partial correlation with the variable that has been input to the model. The variable tha has been inputted to the model can be removed again [7].

4.6. GSTAR Model Validation

Model validation is done to determine the quality of the model and the accuracy of data prediction by finding the value of root mean square error (RMSE):

\[
RMSE = \sqrt{\frac{\sum_{t=2}^{n}(\hat{Z}_t - Z_t)^2}{n}}.
\]

5. Result and Discussion

5.1. The Stationarity of Rainfall Data

First step to the GSTAR modeling was to identify whether not the data were stationary. The results of ADF testing show that the simultaneously the rainfall data from six sub-districts in Sragen regency with zero hypothesis were stationary as indicated by the statistical value of ADF-Fisher-Chi-square = 116.123 with the probability value = 0.000 and with \( \alpha = 0.05 \); the rainfall data in seven areas of Karanganyar Regency were stationary as shown by the the statistical value of ADF – Fisher Chi-square = 68.5407 with the probability value = 0.000 and with \( \alpha = 0.05 \); and the rainfall data in seven areas of Klaten Regency were stationary as signified by the statistical value of ADF – Fisher Chi-square = 65.5407 with the probability value = 0.000 and with \( \alpha = 0.05 \).
5.2. Vector Autoregressive (VAR)
Following the stationarity of rainfall data, they were then then identified into the model of VAR order \( p \). Widarjono [13] claims that identifying VAR model order is done with optimum length of lag. The criteria to determine the optimum length of lag uses the smallest value of Akaike Information Criterion (AIC). According to Tsay [12], AIC can be formulated as follows:

\[
AIC(i) = \ln\left(\frac{J_{KS}}{T}\right) + \frac{2k^2i}{T}
\]

where \( J_{KS} \) is the value of quadratic residue, \( T \) is the number of observation, and \( k \) is the number of model parameter. The values of AIC of each lag for rainfall in the areas of Sragen Regency are presented in Table 1.

| Lag | AIC   |
|-----|-------|
| 0   | 69.4  |
| 1   | 69.4  |
| 2   | 69.8  |
| 3   | 70.3  |
| 4   | 70.6  |
| 5   | 70.8  |
| 6   | 71.3  |

The values of AIC of each lag for rainfall of the areas of Karanganyar Regency are presented in Table 2.

| Lag | AIC   |
|-----|-------|
| 0   | 88.97 |
| 1   | 87.1  |
| 2   | 87.4  |
| 3   | 87.6  |
| 4   | 87.9  |
| 5   | 88.2  |
| 6   | 88.4  |

The values of AIC of each lag for rainfall in the areas of Klaten Regency are presented in Table 3.

| Lag | AIC   |
|-----|-------|
| 0   | 80.7  |
| 1   | 80.2  |
| 2   | 80.1  |
| 3   | 80.6  |
| 4   | 80.6  |
| 5   | 80.1  |

According to Table 1 and Table 2, the least value of AIC were 69.4 and 87.305 respectively on lag 1, so that the model order of VAR was 1 on the data of Sragen Regency and Karanganyar Regency. The least value of AIC in Table 3 was 80.079 on lag 5 so that the model order of VAR was 5. Wutsqa et al. [14] identify autoregressive order into GSTAR model by using order from VAR model. Thus, GSTAR model autoregressive orders were 1 and 5.

5.3. Generalized Space Time Autoregressive (GSTAR) Model
The Model of GSTAR as the development of STAR model is as follows:

\[
Z_{it} = \sum_{k=1}^{p} \sum_{l=0}^{s} \sum_{t=1}^{n} \Phi_{kl} W_{i} Z_{tk} + e_{it}
\]

where \( Z_{it} \) is observation of area \( i \) in time of \( t \), \( \Phi_{kl} \) is diagonal space time matrix with spatial lag of 1 and \( k \) is value of time lag on area of \( i \), \( W \) is weighting matrix, and \( e_{it} \) is normal residue. Spatial order 1 is choosen in the establishment of this model for the ease of interpretation. Autoregressive order 1 is for the areas of Sragen Regency and Karanganyar Regency (GSTAR model (1_1)) and autoregressive order 5 is for the areas of Klaten Regency Regency (GSTAR model (5_1)). The establishment of GSTAR model (1_1) and (5_1) with normalized cross correlation location weighting was then applied on the rainfall data for the areas of Sragen Regency, Karanganyar Regency, and Klaten Regency.
5.4. GSTAR Model for the Rainfall in the Areas of Sragen Regency

GSTAR model was established by choosing the weighting result from normalized cross correlation between locations on corresponding lags. The establishment of this weighting factor as claimed by Suhartono and Subanar [10] can be obtained from:

\[ W_{ij}(k) = \frac{r_{ij}(k)}{\sum_{k=1}^{p} r_{ik}(k)} \]

with \( i = j, k = 1,2,...,p \) and

\[ r_{ij}(k) = \sum_{t=k+1}^{n} \frac{[Z_i(t) - \bar{Z}_i][Z_j(t-k) - \bar{Z}_j]}{\sqrt{\sum_{t=1}^{n} [Z_i(t) - \bar{Z}_i]^2 \sum_{t=1}^{n} [Z_j(t) - \bar{Z}_j]^2}} \]

The calculation of weighting factor in this model resulted in:

\[
W = \begin{bmatrix}
0 & 0.192 & 0.198 & 0.199 & 0.214 & 0.197 \\
0.205 & 0 & 0.195 & 0.196 & 0.202 & 0.201 \\
0.206 & 0.179 & 0 & 0.198 & 0.209 & 0.209 \\
0.183 & 0.195 & 0.206 & 0 & 0.219 & 0.196 \\
0.210 & 0.188 & 0.194 & 0.215 & 0 & 0.194 \\
0.199 & 0.177 & 0.215 & 0.198 & 0.212 & 0
\end{bmatrix}
\]

Based on the weighting matrix above, the estimation of model parameter was done by using the least square method and by testing the significance value of each model parameter. Then estimation of regression parameter with stepwise procedure was done to achieve a good model. The result of parameter estimation and its significance test are as follows:

| Predictor | Parameter Est. | p-value | Conclusion |
|-----------|----------------|---------|------------|
| \( Z_0(t-1) \) | 0.80479 | 0.000 | Significant |
| \( w_1(t-1) \) | 0.77650 | 0.000 | Significant |
| \( w_2(t-1) \) | 0.66548 | 0.000 | Significant |
| \( w_3(t-1) \) | 0.73035 | 0.000 | Significant |
| \( w_4(t-1) \) | 0.85165 | 0.000 | Significant |
| \( w_6(t-1) \) | 1.22659 | 0.000 | Significant |

\[ Z_{it} = 0.805 Z_0(t - 1) + 0.776 w_1(t - 1)Z_i(t - 1) + 0.665 w_2(t - 1)Z_i(t - 1) + 0.730 w_3(t - 1)Z_i(t - 1) + 0.852 w_4(t - 1)Z_i(t - 1) + 1.23 w_6(t - 1)Z_i(t - 1), \]

for \( i \neq j, Z_{ij} = 0, w_i \) is the weighting value of the first row.

Then following the the inputing of weighting value, the following was obtained:
Based on the above six prediction models, a conclusion is drawn that the rainfall prediction in Masaran area in month \( t \) was slightly affected by the rainfall condition of a month earlier in other areas around it, namely: the areas of Ngrampal, Tanon, Karangmalang, Plupuh, and Kedawung. It also happened in the areas of Ngrampal, Tanon, Karangmalang and Kedawung. However, the rainfall prediction in Plupuh area in month \( t \) was only affected by the rainfall condition of a month earlier in its own area.

5.5. GSTAR Model for the Rainfall in the Areas of Karanganyar Regency

In the forming of GSTAR model (1) based on the rainfall data in several areas of Karanganyar Regency, the following weighted normalized cross-correlation was gained:

\[
W = \begin{bmatrix}
0 & 0.052 & 0.212 & 0.213 & 0.104 & 0.238 & 0.181 \\
0.111 & 0 & 0.118 & 0.173 & 0.036 & 0.433 & 0.128 \\
0.193 & 0.064 & 0 & 0.061 & 0.263 & 0.109 & 0.309 \\
0.303 & 0.096 & 0.087 & 0 & -0.066 & 0.365 & 0.083 \\
0.096 & -0.012 & 0.371 & -0.107 & 0 & -0.092 & 0.322 \\
0.235 & 0.14 & 0.114 & 0.313 & -0.069 & 0 & 0.130 \\
0.189 & 0.088 & 0.291 & 0.057 & 0.254 & 0.121 & 0
\end{bmatrix}
\]

With the least square method and the above stepwise procedure the following result was obtained:

| Predictor | Parameter Est. | p-value | Conclusion |
|-----------|----------------|---------|------------|
| \( Z_1(t-1) \) | 0.60829 | 0.000 | Significant |
| \( Z_2(t-1) \) | 0.4758 | 0.047 | Significant |
| \( Z_3(t-1) \) | 0.3517 | 0.048 | Significant |
| \( Z_4(t-1) \) | 0.58262 | 0.000 | Significant |
| \( Z_5(t-1) \) | 0.61669 | 0.000 | Significant |
| \( Z_6(t-1) \) | 0.3595 | 0.049 | Significant |
| \( Z_7(t-1) \) | 0.4061 | 0.014 | Significant |
| \( w_1(t-1) \) | 0.2757 | 0.017 | Significant |
| \( w_2(t-1) \) | 0.4168 | 0.017 | Significant |
| \( w_3(t-1) \) | 0.3771 | 0.023 | Significant |
| \( w_4(t-1) \) | 0.6441 | 0.000 | Significant |
| \( w_5(t-1) \) | 0.3699 | 0.049 | Significant |
| \( w_6(t-1) \) | 0.4017 | 0.023 | Significant |
Next, following the inputting of the weighting value, the following was obtained:

\[
Z_{tt} = 0.608 Z_1(t-1) + 0.476 Z_2(t-1) + 0.352 Z_3(t-1) + 0.583 Z_4(t-1) + 0.617 Z_5(t-1) + 0.359 Z_6(t-1) + 0.406 Z_7(t-1) + 0.276 w_1(t-1)Z_1(t-1) + 0.417 w_3(t-1)Z_1(t-1) + 0.377 w_4(t-1)Z_1(t-1) + 0.644 w_5(t-1)Z_1(t-1) + 0.370 w_6(t-1)Z_1(t-1) + 0.402 w_7(t-1)Z_1(t-1).
\]

The above result shows that rainfall prediction in the areas of Kebak Kramat, Karanganyar, Mojogedang, Karangpandan, Matesih and Tasik Madu in month \( t \) was mainly affected by the rainfall condition of a month earlier in their own areas and slightly affected by the other areas. However, for the area of Jaten, the rainfall prediction in month \( t \) was only affected by the rainfall condition of a month earlier in its own area.

5.6. **GSTAR Model for the Rainfall in the Areas of Klaten Regency**

For captions not placed at the side of the figure, captions should be set to the width of the figure for wider figures, centred across the width of the figure, or, for narrow figures with wide captions, slightly extended beyond the width of the figure. The caption should finish with a full stop (period).

In the forming of GSTAR model (1.1) based on the rainfall data in several areas of Klaten Regency with the same method, five weighted normalized cross-correlations were gained. With the least square method and stepwise procedure, the following result was obtained:

**Table 6. Value of parameter estimation model, p value and conclusion**

| Predictor | Parameter Est. | p-value | Concl. |
|-----------|----------------|---------|--------|
| \( Z_1(t-1) \) | 0.74698 | 0.000 | Significant |
| \( Z_5(t-1) \) | 0.81455 | 0.000 | Significant |
| \( Z_6(t-1) \) | 0.5716 | 0.000 | Significant |
| \( w_2(t-1) \) | 0.84643 | 0.000 | Significant |
| \( w_3(t-1) \) | 0.84914 | 0.000 | Significant |
| \( w_4(t-1) \) | 0.95450 | 0.000 | Significant |
| \( w_7(t-1) \) | 0.79146 | 0.000 | Significant |
| \( w_6(t-2) \) | 0.4992 | 0.001 | Significant |
| \( w_6(t-4) \) | 0.2601 | 0.029 | Significant |

\[
Z_{tt} = 0.747 Z_1(t-1) + 0.815 Z_5(t-1) + 0.572 Z_6(t-1) + 0.846 w_2(t-1)Z_1(t-1)
\]
\[ +0.849 \, w_2(t-1)Z_i(t-1) + 0.954 \, w_4(t-1)Z_i(t-1) + 0.791 \, w_7(t-1)Z_i(t-1) \\
+ 0.499 \, w_6(t-2)Z_i(t-1) + 0.260 \, w_6(t-4)Z_i(t-1) \]

Next, by inputting the weightings' value, the following result was obtained:

\[
\begin{pmatrix}
Z_1(t) \\
Z_2(t) \\
Z_3(t) \\
Z_4(t) \\
Z_5(t) \\
Z_6(t) \\
Z_7(t)
\end{pmatrix} = 
\begin{pmatrix}
0.747Z_1(t-1)
0.15Z_1(t-1) + 0.15Z_3(t-1) + 0.14Z_4(t-1) + 0.12Z_5(t-1)
0.17Z_1(t-1) + 0.13Z_2(t-1) + 0.14Z_4(t-1) + 0.14Z_5(t-1)
0.19Z_1(t-1) + 0.14Z_2(t-1) + 0.15Z_3(t-1) + 0.16Z_5(t-1)
0.82Z_5(t-1)
0.57Z_6(t-1) + 0.1Z_1(t-2) + 0.09Z_2(t-2) + 0.08Z_3(t-2) \\
0.14Z_1(t-1) + 0.11Z_2(t-1) + 0.11Z_3(t-1) + 0.13Z_4(t-1)
\end{pmatrix} + 
\begin{pmatrix}
0 \\
0.16Z_6(t-1) + 0.13Z_7(t-1) \\
0.15Z_6(t-1) + 0.12Z_7(t-1) \\
0.17Z_6(t-1) + 0.14Z_7(t-1) \\
0.1Z_4(t-2) + 0.06Z_5(t-2) + 0.07Z_7(t-2) - 0.04Z_1(t-4) \\
0.14Z_5(t-1) + 0.15Z_6(t-1)
\end{pmatrix} + 
\begin{pmatrix}
0 \\
0 \\
0 \\
0 \\
0 \\
0 \\
0
\end{pmatrix}
\]

Interpretation of the above models is that the rainfall prediction in Polanharjo area in month \( t \) was 75 percent affected by the rainfall condition of a month earlier in its own area but it wasn't affected by the areas of Cawas, Trucuk, Karangdowo, Wonosari, Delanggu and Juwiring. However, for the area of Cawas, it wasn't affected by the rainfall condition of a month earlier in its own area but it was slightly affected by the rainfall condition of a month earlier of a month earlier in other areas around it. Condition in Cawas area had the similarity with th condition of Trucuk and Karangdowo areas. Otherwise the rainfall prediction in Wonosari area in month \( t \) was 82 percent affected by the condition in its own area and it wasn't affected by the other around it. For the rainfall prediction in Delanggu area in month \( t \) was 57 percent affected by the rainfall condition of a month earlier in its own area but it was slightly affected by the rainfall condition of two month earlier and four month earlier in other areas around it. The last in the Juwiring area in month \( t \) was slightly affected by the rainfall condition of a month earlier in other areas around it and it was not affected by the condition in its own area.

5.7. Model Validation

To validate the above GSTAR model, the value of RMSE was calculated as one of the model quality measuring tools. GSTAR model (1) for the rainfall in the areas of Sragen Regency had the RMSE value of 155.1631. The GSTAR model (1) for the rainfall in the area of Karanganyar had the RMSE value of 179.1086. GSTAR model (5) for the rainfall in the area of Klaten had the RMSE value of 141.6979.

6. Conclusion

The rainfall conditions of the sixth areas of rice production areas of Sragen regency in month \( t \) only were affected by the rainfall condition of a month earlier. From the sixth areas in Sragen only Plupuh area was affected by the rainfall condition in its own area which were significant at \( \alpha = 5\% \).
Then the rainfall conditions in month $t$ of the seventh areas of rice production areas of Karanganyar regency only were affected by the rainfall condition of a month earlier and only in Jaten area was affected by the rainfall condition in its own area which were significant at $\alpha = 5\%$.

But the rainfall conditions in month $t$ of the seventh areas of rice production areas of Klaten regency were affected by the rainfall condition of a month earlier, two month earlier, and four month earlier. The rainfall conditions in Polanharjo, Wonosari and Delanggu areas were affected by the rainfall condition of a month earlier in its own areas and they were slightly affected by the rainfall condition in other areas around it. While the rainfall conditions in month $t$ in Cawas, Trucuk and Karangdowo weren’t affected by the rainfall condition in its own areas but they were slightly affected by the its condition in other areas around them which were significant at $\alpha = 5\%$.

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