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ROBUST SPATIAL TEMPORAL ANALYSIS WITH IMPROVED GEOGRAPHICALLY AND TEMPORALLY WEIGHTED REGRESSION MODEL OF DENGUE INCIDENCE RATE

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Abstract: Improved Geographically and Temporally Weighted Regression (IGTWR) is a development of Geographically Weighted Regression (GWR) which involves elements of time and spatial-temporal interactions to see the effect of distance measured in spatial dimensions on temporal distance in modeling formation. This method produces a local model at each location, time, and also considers interactions in the dimensions of space and time so that the resulting model is more representative and compatible. IGTWR model parameters estimated using the WLS method are not robust to outliers. This can result in biased regression models and errors in concluding relationships between variables. Robust regression modeling with the M estimator developed in the IGTWR model and applied to the incidence of dengue hemorrhagic fever in South Sulawesi Province from 2016 to 2021 can overcome the outlier problem that occurred at the location and time studied. This is indicated by the predicted value of the RIGTWR model being closer to the actual value than the IGTWR model, a decrease in the RMSE and MAD values, and an increase in the Adjusted R Square value.

Keywords: Spatial-Temporal; M-Estimator; Robust Improved Geographically and Temporally Weighted Regression; Dengue Incidence Rates.

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1. INTRODUCTION

The World Health Organization (WHO) states that Dengue Hemorrhagic Fever (DHF) is a significant public health problem globally. Every year, it is estimated that there are around 390 million new dengue virus infections worldwide. Over 25% of people worldwide are at risk of contracting dengue fever [1]. In particular, South Sulawesi Province had the highest dengue fever incidence rate in 2016 at 89 cases per 100,000 population and always experienced increases and decreases until in 2021, the dengue incidence rate increased from the previous year 29-30 dengue fever cases increased to 39 cases per 100,000 population [2], [3]. To overcome this increase, it is necessary to know the factors that influence the incidence of dengue fever. The main factors influencing several Provinces in Indonesia include poverty, population density, and health facilities [4], [5].

Dengue fever often has a spatial distribution pattern showing that certain areas tend to differ from others [6]. Apart from that, differences in regional conditions and changes in time that cause a reduction in the number of dengue fever incidents in a region cannot be analyzed using the same analytical approach. Therefore, to identify the components that contribute to the influence at a location over a period of time, spatial and temporal methods are used. The spatial-temporal modeling method that can be used is Geographically and Temporally Weighted Regression (GTWR) [7]-[9]. However, the GTWR method uses a summation operator to model spatial-temporal distance. As a result, this can cause the modeling of spatial-temporal interactions to be less precise because the temporal distance is unaffected by the geographical dimension distance. To overcome this, the GTWR model was developed by adding spatial-temporal distance interactions by modifying the distance function using the Improved Geographically and Temporally Weighted Regression (IGTWR) model [10], [11].

IGTWR model parameters are estimated using the WLS method. This method is not robust and efficient in handling outliers, which will result in biased regression modeling and errors in inferring the relationship between variables [12], [13]. Therefore, an IGTWR model using M-estimator is needed to accommodate outlier data. M-estimator is a robust and efficient estimation method for outliers introduced by Huber (1973). This method analyzes data by assuming that most outliers are detected in the response variable and is the simplest estimate both computationally and theoretically [14]. Therefore, the purpose of this study is to use the M-estimator to create a robust improved geographically and temporally weighted regression (RGTWR) model.

2. PRELIMINARIES

A. Cases Dengue Incidence Rate

This research uses secondary data, namely the incidence of dengue fever, population density, percentage of poor population, number of health facilities, and percentage of access to proper sanitation obtained from the South Sulawesi Provincial Health Service and publications from the Central Statistics Agency (BPS) in the 2016-2021 period. The identification of the variables utilized is explained in Table 1.

Table 1. Data Identification

Variables	Descriptions	Units
Y	Dengue Incidence Rate	People per 100,000 population
X_1	Population density	Jiwa/km^2
X_2	Percentage of Poor Population	%
X_3	Number of Health Facilities	Unit
X_4	Percentage of Access to Proper Sanitation	%

B. Heterogeneity Test

Testing for spatial diversity can be done with the Breusch Pagan test (BP). According to Anselin [15], this test has the following hypothesis:

$\mathrm{H}_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (There is no spatial diversity between locations)

$\mathrm{H}_1 :$ There's at least one $\sigma_i^2 \neq \sigma_j^2$ for $i, j = 1,2, \dots, p$ (There is spatial diversity between locations)

BP test statistics are shown in Equation 1.

$$BP = \frac{1}{2}\boldsymbol{f}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{f} \sim \chi^2_{(\alpha,p)} \tag{1}$$

where vector $\boldsymbol{f}$ is $f_i = \left(\frac{\varepsilon_i^2}{\sigma^2} - 1\right)$, $\boldsymbol{Z}$ is a response variable matrix measuring $n \times (p+1)$ which contains a standard vector for each observation with $i = 1,2,\dots.,n$, ε_i^2 is the mean squared error for the i^{th} observation and σ^2 is the variance ε_i. The BP test statistic has $\chi^2_{\alpha,p}$ distribution where p is the number of regression parameters. The decision to reject H_0 is when the BP value is greater than $\chi^2_{\alpha,p}$ which means there is spatial diversity.

C. Outlier Detection

Outliers are observed values that do not follow the data distribution pattern but removing them is not a good decision [16]. Therefore, it is necessary to identify outliers in the data. One of good methods for detecting outliers is Studentized Deleted Residuals or what can be called Jack-Knife Residuals in [17] with the formula according to Equation 2.

$$t_i = r_i\sqrt{\frac{n-p-1}{n-p-r_i^2}} \tag{2}$$

where r_i is i^{th} standardized residuals according to Equation 3 [18].

$$r_i = \frac{\hat{\varepsilon}_i}{\sqrt{MSE(1-h_{ii})}} \tag{3}$$

where $MSE = \sqrt{SSE/n-p-1}$ is the mean of the squared errors and $h_{ii} = \boldsymbol{x}_i'(\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X})^{-\mathbf{1}}\boldsymbol{x}_i$ is a leverage value that can be said to be an outlier to the predictor variable. This leverage value was identified as an outlier when the value $h_{ii} > \frac{2p}{n}$ [19]. Meanwhile, the data was identified as an outlier using the jack-knife residuals method when the value $|t_i| > t_{\frac{\alpha}{2},n-p-1}$.

D. Improved Geographically and Temporally Weighted Regression

The IGTWR model is a development of the GTWR method in spatially weighted regression with the addition of spatial-temporal distance interactions in the distance function. Thus, the distance measured in the spatial dimension affects the temporal distance, making it suitable for modeling spatial-temporal interactions [11], [20]. According to Djuraidah [21], the IGTWR model with p is the number of predictor variables x_i and response variable y_i at location (u_i, v_i, t_i) for each observation written in Equation 4.

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \tag{4}$$

with $\beta_0(u_i, v_i, t_i)$ is intercept at observation location (u_i, v_i) and time t_i, $\beta_k(u_i, v_i, t_i)$ is regression coefficient of the k^{th} predictor variables at the i^{th} observation location and time t_i, and ε_i is error in the location of the i^{th} observation. The parameter estimates can be written in Equation 5.

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-\mathbf{1}} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y} \tag{5}$$

where $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$ and $\boldsymbol{W}(u_i, v_i, t_i)$ is the weighting matrix on observations (u_i, v_i) at time t_i. Wu, Li, dan Huang (2014), defines the spatial-temporal distance function of the IGTWR model in Equation 6.

$$\begin{cases} d_{ij}^{ST} = d_{ij}^{S} \otimes d_{ij}^{T} = \lambda d_{ij}^{S} + \mu d_{ij}^{T} + 2\sqrt{\lambda \mu d_{ij}^{S} d_{ij}^{T}}\, cos\,(\xi) & , t_i < t_j \\ d_{ij}^{ST} = \infty & , t_i > t_j \end{cases} \tag{6}$$

where t_i and t_j is the observation time at the i^{th} and j^{th} locations. The parameters λ, μ, dan $\xi \in [0, \pi]$ are balancing parameters obtained by optimizing the coefficient of determination through the Cross Validation (CV) procedure using the formula according to Equation 7.

$$CV = \sum_{i=1}^{n} (y_i - \hat{y}_{\neq i})^2 \tag{7}$$

where $\hat{y}_{\neq i}$ is the estimated value from the IGTWR model without involving the i^{th} location.

E. Robust Improved Geographically and Temporally Weighted Regression

Robust regression on the RIGTWR model is performed by multiplying the robust weights with the temporal spatial weights formed from the estimation results in Equation 5. The RIGTWR model for the i^{th} location containing outliers corresponds to Equation 8.

$$\rho(y_i) = \rho\left[\beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i\right] \tag{8}$$

where $i = 1,2,3, \dots, n$ and $x_{ik} = x_{i1}, x_{i2}, \dots, x_{ip}$

The process of doing robust regression using the M-estimator involves minimizing the objective function of the error according to Equation 9

$$\hat{\beta}_M = \min_{\beta} \sum_{i=1}^{n} \rho(\varepsilon_i) = \min_{\beta} \sum_{i=1}^{n} \rho\left(y_i - \boldsymbol{X}_i^T \widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)\right) \tag{9}$$

M-estimation using the Iteratively Reweighted Least Square (IRLS) method. In this iteration, the value of the robust weight w_i^* will change its value in each iteration and is multiplied by the spatial weight $\boldsymbol{W}$ to form the spatial robust weight $\boldsymbol{w}^*$ according to Equation 10.

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)^m = \left(\boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m-1})\boldsymbol{X}_i\right)^{-1} \boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m-1})\boldsymbol{y}_i \tag{10}$$

So, if the weight $\boldsymbol{w}^{*m}$ is given, we get an estimate of Equation 11.

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)^{m+1} = (\boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m})\boldsymbol{X}_i)^{-1} \boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m})\boldsymbol{y}_i \tag{11}$$

where m is the iterations count [22].

M-estimator weighting algorithm in the IGTWR model:

a. Calculating $\hat{y}_i = \boldsymbol{x}_i^T \widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ from the IGTWR model
b. Calculate the error value $\varepsilon_i = y_i - \hat{y}_i$
c. Calculate the values of $z_i = \varepsilon_i / \hat{\sigma}_M$ and $\hat{\sigma}_M$ according to Equation 12.

$$\hat{\sigma}_M = \frac{median|\varepsilon_i - median(\varepsilon)|}{0.6745} \tag{12}$$

d. Calculate the robust weight value (w_i^*) using the weighting function according to Equation 13

$$w_i^* = \begin{cases} \left(1 - \left(\frac{z_i}{c}\right)^2\right)^2 & , |z_i| \le c \\ 0 & , |z_i| > c \end{cases} \tag{13}$$

where a tuning constant value of $c = 4.685$

e. Calculating $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)^m = \left(\boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m-1})\boldsymbol{X}_i\right)^{-1} \boldsymbol{X}_i^T(\boldsymbol{W} \times \boldsymbol{w}^{*m-1})\boldsymbol{y}_i$

Repeat steps (a) to (e) until a convergent estimate is obtained, namely when the difference in the values of $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)^{m+1}$ and $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)^m$ approaching the value of 0.001.

3. MAIN RESULTS

A. Description of Dengue Incidence Rate in South Sulawesi

The incidence of dengue fever is one of the health problems that needs attention. The number of dengue fever sufferers from year to year shows a large number, even becoming one of the diseases that cause the most deaths worldwide, including in Indonesia, especially South Sulawesi Province. A description of the dengue incidence rate in South Sulawesi from 2016 to 2021 is shown in Table 2.

Table 2. Description of Dengue Incidence Rate Data in South Sulawesi

Years	**Maximum**	**Minimum**	**Mean**	**Median**	**Standard Deviation**
2016	283	3	102.30	89.00	74.16
2017	83	0	23.79	12.50	24.21
2018	76	3	28.50	25.50	19.83
2019	147	0	47.46	38.50	42.53
2020	119	2	34.29	21.50	32.89
2021	202	3	45.50	41.00	45.82

Table 2 shows that the annual median, mean, and standard deviation of the dengue incidence rate in South Sulawesi has decreased and increased. In 2016, the average number of dengue fever sufferers showed the largest number, as well as the largest standard deviation value. This means that the number of dengue fever sufferers in regency/city in South Sulawesi had the greatest diversity in 2016. Furthermore, Pangkep Regency was the region with the highest number of dengue incidence rate in the 2 years of observation, namely 2016 and 2019, respectively at 283 and 147 cases. In 2017 it was replaced by the Bantaeng Regency with a dengue incidence rate of 73 cases. Parepare City was the area with the highest number of dengue incidence rate in the 2 years of observation, namely 2018 and 2020 with 76 and 119 cases respectively. In 2021 it was replaced by the Sidrap Regency with a dengue incidence rate of 202. This can be seen in Figure 1.

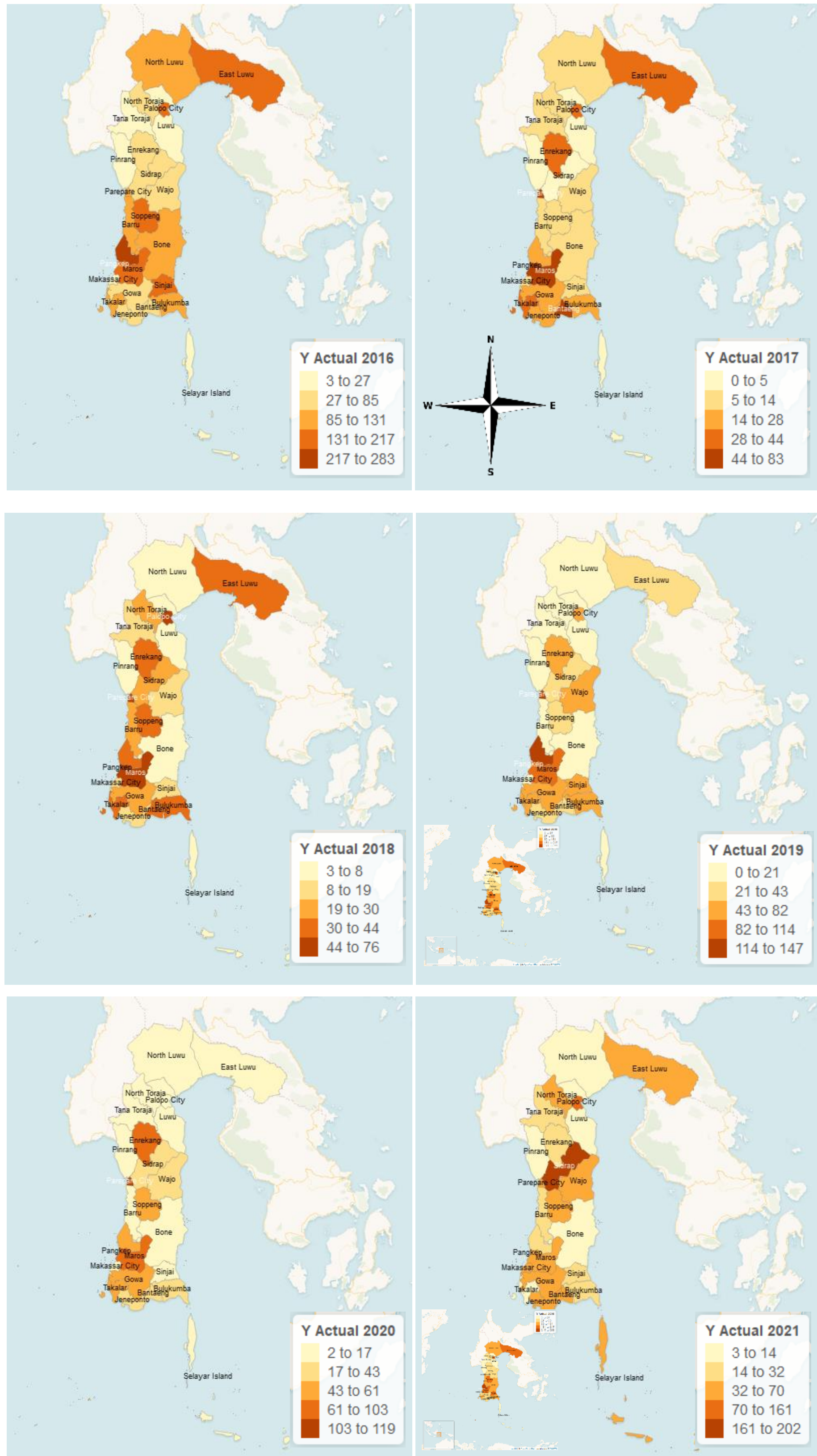

Figure 1. Distribution of Data on Dengue Incidence Rate

B. Spatial and Temporal Heterogeneity Test

Testing for homogeneity of variance using the BP test was carried out to determine whether there was variation due to spatial influences. The test was carried out based on time series, cross section, panel, and simultaneous data types for 24 regencies/cities in South Sulawesi Province in the period of 2016 to 2021. The results of the BP Test are presented in Table 3.

Table 3. Breusch-Pagan Statistical Test

Data Type	**Breusch-Pagan p Value**
Time Series	0.000
Cross section	0.015
Panel	0.000
2016-2021	0.005

Table 3 shows that observations made based on the type of time series, cross section, and panel data show the existence of spatial and temporal diversity in the DHF incidence rate in South Sulawesi. If tested simultaneously, there is spatial and temporal diversity in the data on dengue incidence rates in South Sulawesi from 2016 to 2021. The inequality of spatial and temporal variation is thought to be due to differences in characteristics at each location and at different periods of time.

C. Outlier Detection

Outlier detection using the jack-knife residuals method in Figure 2 resulted in 12 regencies/cities identified as outliers in the IGTWR model residuals for the six years of observation. The calculation of the jack-knife residuals value is shown in table 4.

Table 4. Value of Jack-Knife Residuals

No.	**Location**	**Year**	$\mathbf{|t_i|}$
1	Jeneponto	2016	2.979
2	Selayar Island	2016	3.235
3	Palopo City	2016	3.303

No.	Location	Year	$\lvert t_i \rvert$
4	Luwu	2016	2.277
5	Pangkep	2016	4.358
6	Pinrang	2016	3.276
7	Sinjai	2016	3.329
8	Soppeng	2016	2.843
9	Parepare City	2019	2.507
10	Pangkep	2019	2.914
11	Palopo City	2021	3.575
12	Sidrap	2021	4.823

Table 4 shows that in 2016 there were 7 regions detected as outliers, namely Jeneponto, Selayar Island, Palopo City, Luwu, Pangkep, Pinrang, and Sinjai. In 2019 there were 2 regions detected as outliers, namely Parepare City and Pangkep. In 2021, there are 2 regions detected as outliers, namely Palopo City and Sidrap. While in 2017, 2018, and 2020 there were no outliers. For more clarity, it can be seen in Figure 2.

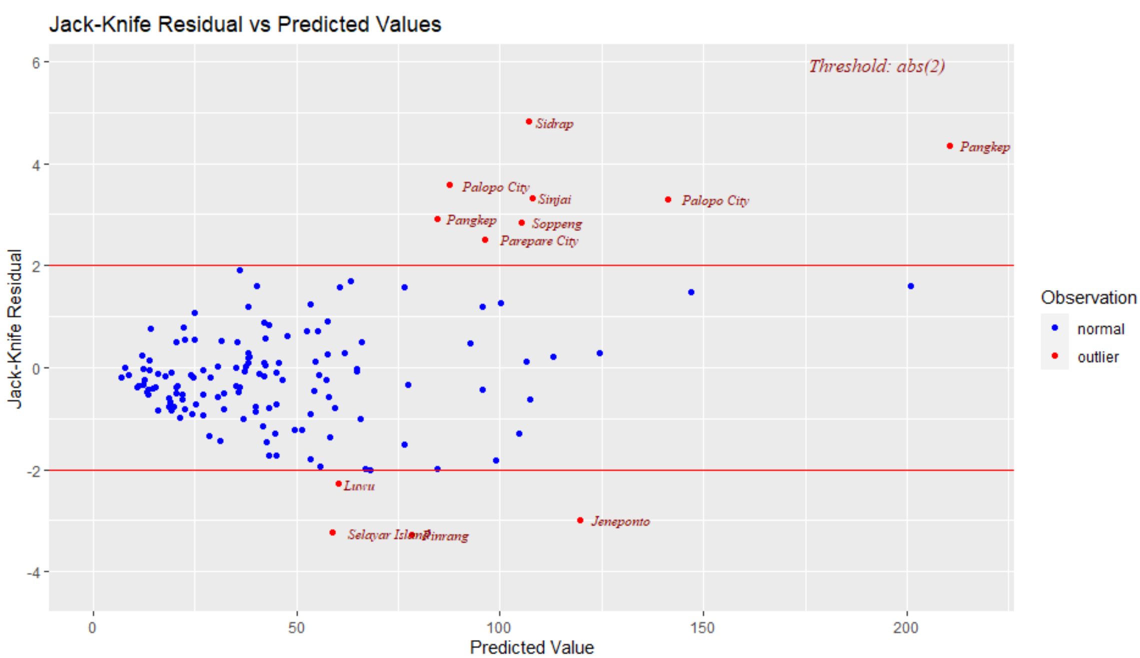

Figure 2. Plot of Jack-Knife Residuals Method

Figure 2 shows the jack-knife residuals method plot. It can be seen that the Pangkep and Sidrap areas have points that are very far from the normal data distribution compared to the others. This shows that these two regions greatly influence the regression model that is formed. Therefore, to overcome the presence of outliers that can affect the model, the RIGTWR method is used using M-estimator.

D. Robust Improved Geographically and Temporally Weighted Regression Modeling

RIGTWR modelling is performed through an iteration process with the IGTWR model parameter estimation results used as initial values. Model parameters are estimated by multiplying the iterated robust weight matrix with IGTWR spatial-temporal weights. The iteration process to generate robust weights uses the M-estimator until the parameter values at iteration m and $m+1$ are close to zero. Each location and time produce a different number of iterations. Therefore, the maximum iteration is determined according to the most iterations from each location and time with a convergence rate used of 0.001. The following will explain the results of RIGTWR modeling by displaying the distribution of coefficients which shows the magnitude of the influence of the predictor variables.

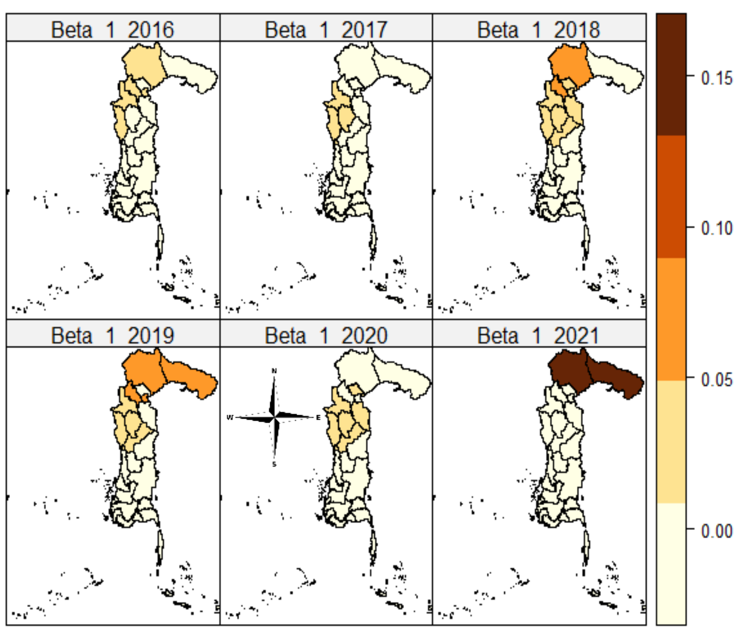

Figure 3. Map of Population Density Coefficient Distribution (X_1)

The results from Figure 3 show that regency/city in the northern regional group has a greater influence on population density on the dengue incidence rate compared to southern regions. It can be seen that in 2021, North Luwu and East Luwu will have the highest influence on population density on the dengue incidence rate. One of the contributing factors is the area. North Luwu and East Luwu Regencys are among the largest regencies in South Sulawesi with percentages of 16% and 15% respectively, so the dengue virus has a high chance of surviving, which will facilitate the spread of the virus resulting in an increase in the dengue incidence rate.

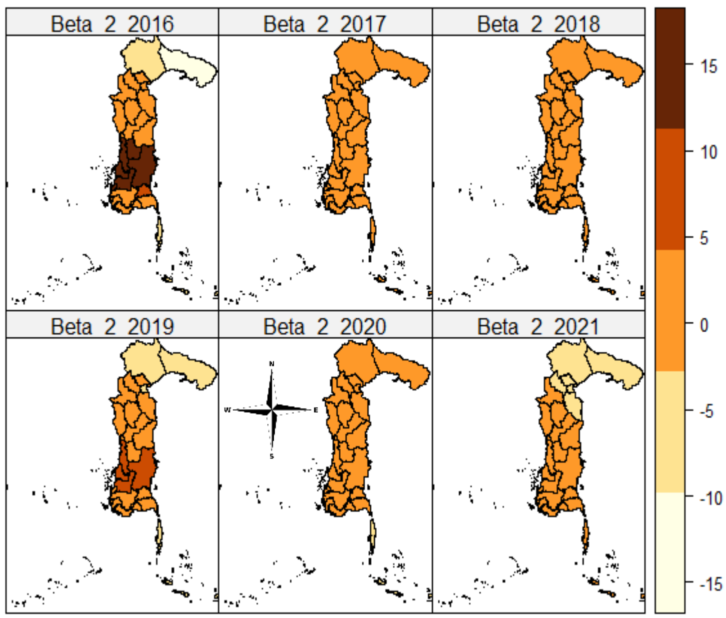

Figure 4. Map of The Distribution of The Coefficient on The Percentage of Poor Population (X_2)

Figure 4 shows that most regions from 2016 to 2020 have a positive influence. This means that if the percentage of poor population increases in an area, it will increase the dengue incidence rate in that area. In 2016, the areas of Barru, Bone, Pangkep, Maros and Makassar City had the highest influence of poor residents on the dengue incidence rate.

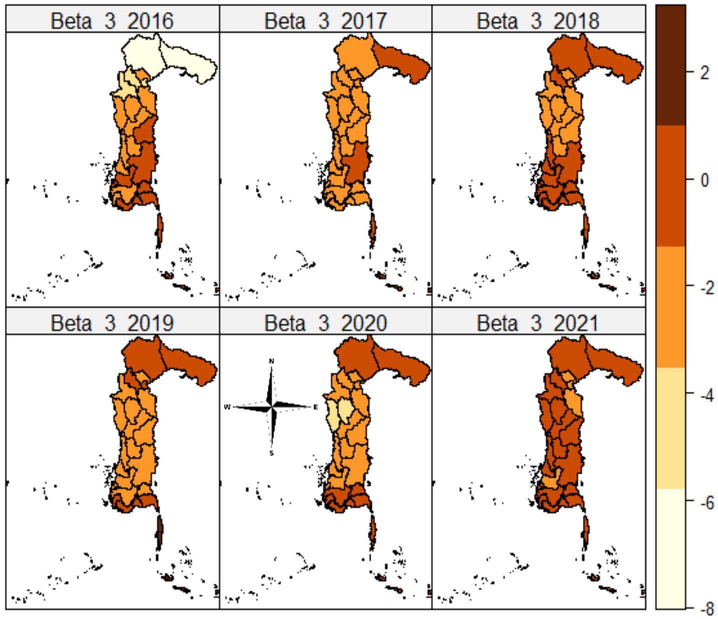

Figure 5. Map of Coefficient Distribution of Number of Health Facilities (X_3)

Figure 5 shows that most regions from 2016 to 2021 have a negative influence. This means that if the number of health recommendations increases in a food area, it will reduce the dengue incidence rate in that area. As seen in 2016, North Luwu and East Luwu regency had the greatest influence on the dengue incidence rate with a negative influence.

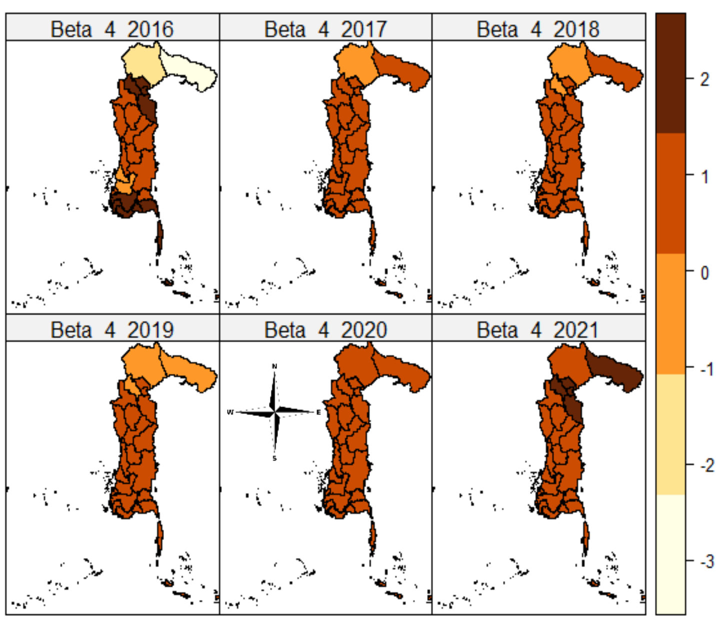

Figure 6. Distribution Map of The Percentage Coefficient of Access to Proper Sanitation (X_4)

Figure 6 shows that large regions from 2016 to 2020 have a positive influence, except for the North Luwu and East Luwu regions in 2016 and North Luwu in 2017 which show highest influence on the dengue incidence rate with a negative influence. This means that if the percentage of access to proper sanitation increases in a food area, it will reduce the dengue incidence rate in that area. Next, a comparison of the actual and predicted dengue incidence rate in South Sulawesi in 2016 was performed using the GTWR and RGTWR models shown in Figure 7.

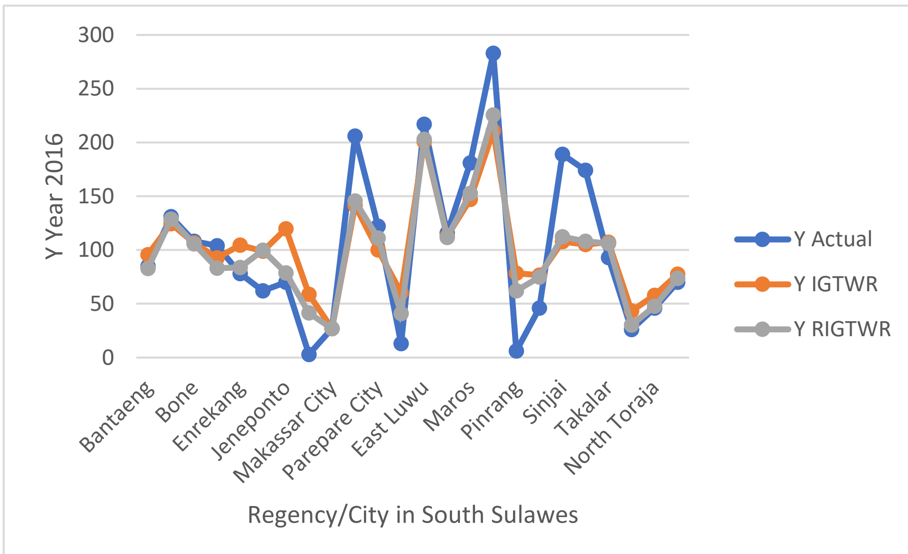

Figure 7. Graph of Actual Data, IGTWR and RIGTWR Model Predictions from Dengue Incidence Rate of South Sulawesi 2016

Figure 7 shows the difference between the predicted values of the IGTWR and RIGTWR models and the actual data. It can be seen that the prediction graph from the RIGTWR model is closer to the actual data compared to the IGTWR model. Hence, the estimator resulting from RIGTWR modeling is able to improve predictions of the dengue incidents rate in South Sulawesi in 2016. Apart from being based on the model comparison graph, it can be shown in Table 5.

Table 5. Comparison of Model Goodness of Fit

Model	**Root Mean Square Error (RMSE)**	**Mean Absolute Deviation (MAD)**	**Adjusted R Square**
IGTWR	38.456	18.677	0.723
RIGTWR	37.970	15.975	0.741

Table 5 shows a statistical comparison of model goodness of fit between the IGTWR and RIGTWR models based on RMSE, MAD and Adjusted R Square values. It can be seen that RIGTWR modeling is able to reduce the RMSE value, which means it is able to reduce the IGTWR model error and can reduce the MAD value, which means the resulting error diversity value is closest to the actual data. Meanwhile, the adjusted R Square RIGTWR value produces a higher value compared to the adjusted R Square IGTWR value of 0.741.

F. Patterns of Contributing Factors in Space and Time

Factors that have a significant influence on the dengue increase rate in the regency/city of South Sulawesi Province using the RIGTWR model M-estimator in the period from 2016 to 2021 are shown in Figure 8.

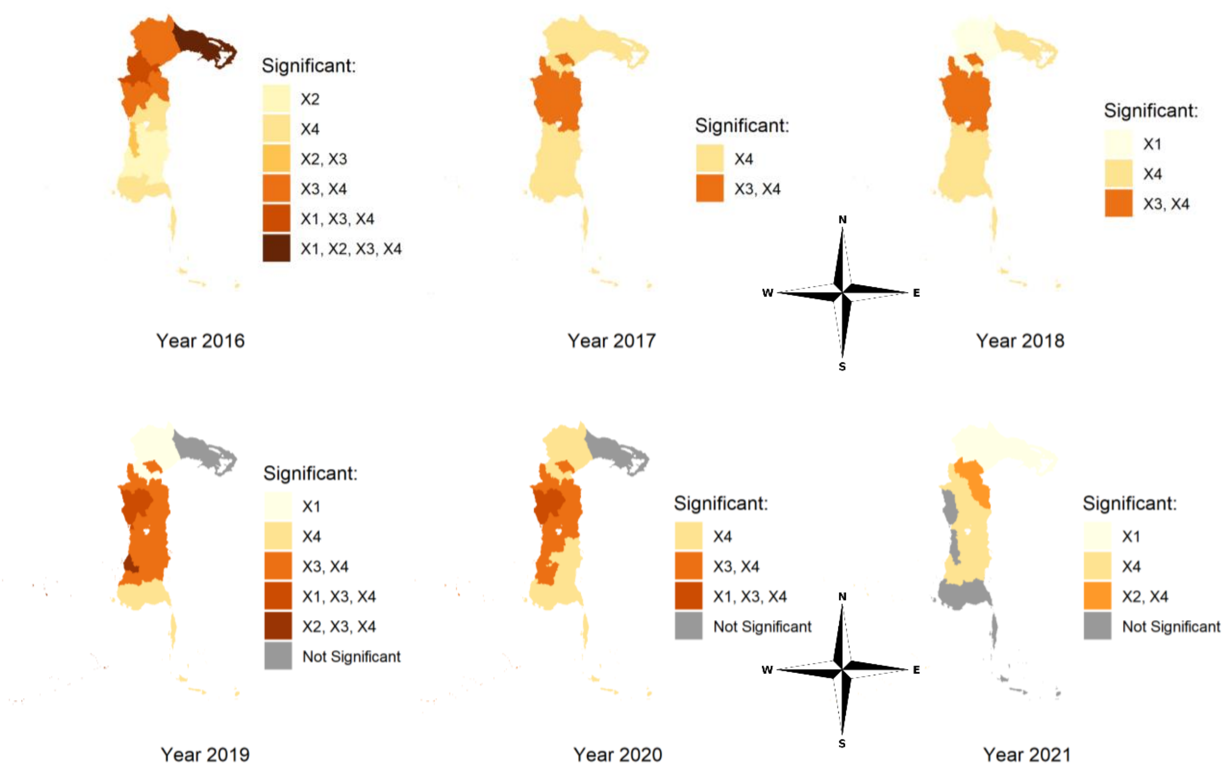

Figure 8 Map of The Influence of Predictor Variables on Response Variables of RIGTWR Model

It can be seen that in the period 2016 to 2021, the factors that are significant to the dengue incidence rate vary by region and year. Category one factors that have a significant effect, namely the percentage of access to proper sanitation, are always consistently influential in the 6 years of the observation period, namely 2016 to 2021. Category two significant factors, namely the number of health facilities and the percentage of access to proper sanitation, are always consistently influential in the 5 years of observation, namely 2016 to 2020. Category three factors that have a significant effect, namely population density, number of health facilities, and percentage of access to proper sanitation, are consistent in the 3 years of observation, namely 2016, 2019, and 2020. While the category of four factors that have a significant effect, namely population density, percentage of poor population, number of health facilities, and percentage of access to proper sanitation, is found in the East Luwu region in 2016.

4. CONCLUSION

Modeling robust spatial-temporal analysis with the RIGTWR model using M estimator can handle data that has outliers well in describing the number of dengue incidence rate in South Sulawesi compared to the IGTWR model using WLS estimation. This is indicated by a decrease in the RMSE, MAD values, and an increase in the adjusted R Square value so the predictions obtained are close to the actual values. Then, the factors found to have an influence on the dengue incidence rate include population density, percentage of poor population, number of health facilities, and percentage of access to proper sanitation. These four factors have a combination of factors that vary by location and time.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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