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Robust Mixed Geographically and Temporally Weighted Regression to Modeling the Percentage of Poverty Population in Java in 2012-2018

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Abstract

Poverty is a fundamental problem in Indonesia, as Java the island with the largest number of poor people. To monitor poverty in regency/municipality in Java Island a model is needed that can explain the diversity of locations and times, such as the GTWR model. Adding global effects to the GTWR model provides a more flexible model and makes interpretation easier, this model is known as MGTWR. Outlier problems in MGTWR as well as in linear regression models can produce biased coefficients. This problem can be solved by adding weight to the error, resulting in the model called RMGTWR. This study aims to model the percentage of poor population data in regency/municipality on Java Island in 2012-2018 and find out the factors that influence it. RMGTWR with bisquare kernel has pseudoR^2 72.73%. Factors that influence significantly on global variables are literacy rates. Whereas, significant local variables are education completed by primary schools, per capita expenditure, recipients of Raskin households, population groups in the age group of 15-64 years, and the average school year are local variables. The coefficient of RMTGWR produces a parameter estimate that is relevant to the trend between poverty and predictors.

Keywords: global and local; RMGTWR; poverty; outliers.

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1. Introduction

Regression analysis is a method used to analyze the linear relationship between several explanatory variables together with a response variable [1]. In OLS (Ordinary Least Square) regression it is assumed that the estimated value of the regression parameter will remain (constant), meaning that the regression parameter is the same value for each point in the study area (global parameters). If there is a spatial diversity in the regression parameters, then the information that cannot be handled by the OLS regression method will be accommodated as an error. Thus, OLS regression is less able to explain the real data phenomenon [2]. One of the ways to solve spatial diversity is using Geographically Weighted Regression (GWR). The GWR model is a development of global regression modeling by adding weight based on the distance from one observation location to another, so that the interpretation for each location point will be different [3]. However, the GWR method in its analysis only considers spatial without time element in its modeling. Therefore, the GWR method was developed into a Geographically and Temporally Weighted Regression (GTWR). The GTWR method will produce a model that is local for each location and time so that the model is more representative [4]. The parameters generated by the GTWR model are local for each location, but the significance test on the model shows that there are insignificant variables (global), while others maintain their spatial influence. Therefore, the GTWR model can be developed into a Mixed Geographically and Temporally Weighted Regression (MGTWR) model. The MGTWR has greater accuracy than the GTWR model in stationary and spatial-temporal non-stationary conditions, as well as the temporal and spatial-temporal predictors of the MGTWR model, are almost consistent with the true values in the simulation data experiments [5]. In practice, some problems are not modeled in MGTWR, such as data outliers. The MGTWR model is not robust to overcome the outliers contained in the data and will result in bias and inaccurate regression relationships. The handling of outliers is carried out by developing the model into a Robust Mixed Geographically and Temporally Weighted Regression (RMGTWR) model. The authors in [6] using Geographic Temporal Weighted Regression (RGTWR), which able to overcome GTWR modeling errors that were detected as outliers in the case of the number of active family planning participants in East Java. Found that RGTWR produces better modeling because it produces parameter estimators that are more in line with the actual data and data plot and have a smaller MAD value. Poverty is a fundamental problem in developing countries like Indonesia. Differences in potential between regions in Indonesia allow a diversity of local and global data together. According to [7] the number of poor people in Indonesia in March 2019 was 25.14 million people with the largest percentage of poor people in the Maluku and Papua regions. But nationally, the largest number of poor people are in Java Island, amounting to 12.56 million people. The problem of poverty is interesting to research to be modeled using the RMGTWR method. This study is constraint to model data that has outliers, temporal influences, spatial effects both locally and globally. Therefore, this study aims to models data on the percentage of poor people in regency/municipality in Java in 2012-2018 and to determine the factors that are suspected to influence them.

2. Materials and Methods

2.1. Data

The data used are in the form of secondary data from BPS-Statistics of Indonesia from 2012 to 2018. The response variable used is the percentage of poor people living in regency/municipality on Java Island. The explanatory variables used are shown in Table 1 as follows:

Table 1: Explanatory Variable

	Description of variables	Reference
X1	Gross Regional Domestic Product (Billion Rupiah)	[8]
X2	People with the highest education graduated from elementary school (%)	[9]
X3	Literacy numbers	[10]
X4	Per capita expenditure for food (%)	[9]
X5	Raskin/rasta recipient households (%)	[10]
X6	Population according to age group 15-64 (%)	[11]
X7	Expected years of schooling (EYS) (Year)	[10]
X8	Mean years of schooling (MYS) (Year)	

2.2. Data Analysis Procedure

The steps of the analysis are as follows:

1. Exploring data on the percentage of poor people in regency/municipality in Java in 2012-2018.
2. Calculating the value of Variance Inflation Factor (VIF) to determine the multicollinearity of the explanatory variables, with criteria if VIF> 10 then multicollinearity occurs between variables.
3. Check spatial diversity annually on data using the Breusch Pagan (BP) test. This test uses the following hypothesis.

H_0: $\beta_2 = \beta_3 = \cdots = \beta_k = 0; k = 1, 2, \ldots, p$

H_1: $\sigma_i^2 \neq \beta_1$=constant; $i = 1, 2, \ldots, n$

The test statistic used is

$$BP = \frac{1}{2}\left(\sum_{i=1}^{n} x_i f_i\right)^T \left(\sum_{i}^{n} x_i x_i^T\right)\left(\sum_{i=1}^{n} x_i f_i\right) \sim \chi^2_{(k-1)}$$

with $f_i = \left(\frac{\hat{z}_i}{\hat{\sigma}} - 1\right)$, $\hat{z}_i = \left(y_i - \hat{\beta}^T x_i\right)$, $\hat{\sigma}^2 = \sum_{i=1}^{n} \hat{z}_i{}^2$

Test criteria used are reject H_0 if the test statistic value $BP > \chi^2_{(k-1)}$ or if the p-value < α with k is the number of parameters [12].

4. Determine global variables and local variables using the confidence interval of the global regression model. Criteria for selection as a global variable if at least 70% of the GTWR coefficients are within the confidence interval [13].

5. Analysis of the mixed GTWR model using the two-stage least squares.

a. Calculates the local parameter estimator from $\widetilde{\boldsymbol{y}}$ [4].

i. Calculates temporal-spatial ratio parameters (τ) and temporal-spatial distance (d_{ij}^{ST}) and the width of the temporal-spatial window (h_{ST}^2) using the Cross-Validation (*CV*) approach.

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

$$\left(d_{ij}^{ST}\right)^2 = \lambda\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \mu\left(t_i - t_j\right)^2$$

ii. Determine the function of the temporal-spatial weighting by using the Bisquare weighting with *i*,*j*= *1*, *2*, …, *n*.

$$w_{ij} = exp\left(-\left(\frac{(d^S)^2}{h_S^2}\right) + \frac{(d^T)^2}{h_T^2}\right)$$

iii. Calculate the weighting

$$\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$$

iv. Calculating local variable estimator [5].

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

b. Update the global variable estimator [5].

$$\widehat{\boldsymbol{\beta}}_g = \left[\boldsymbol{X}_g^T(\boldsymbol{I} - \boldsymbol{S}_l)^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{S}_l)\boldsymbol{X}_g\right]^{-1}\boldsymbol{X}_g^T(\boldsymbol{I} - \boldsymbol{S}_l)^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{S}_l)\boldsymbol{y}$$

$$\boldsymbol{S}_l = \begin{bmatrix} \boldsymbol{x}_{l1}^T(\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}_l)^{-1}\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i) \\ \boldsymbol{x}_{l2}^T(\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}_l)^{-1}\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i) \\ \vdots \\ \boldsymbol{x}_{ln}^T(\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}_l)^{-1}\boldsymbol{X}_l^T\boldsymbol{W}(u_i, v_i, t_i) \end{bmatrix}$$

c. Update local variable estimator.

$$\widehat{\boldsymbol{\beta}}_l(u_i, v_i, t_i) = [\boldsymbol{X}_l^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}_l]^{-1}\boldsymbol{X}_l^T \boldsymbol{W}(u_i, v_i, t_i)\left(\boldsymbol{y} - \boldsymbol{X}_g\widehat{\boldsymbol{\beta}}_g\right)$$

d. Determine the MGTWR model response estimator [8].

$$\widehat{\boldsymbol{y}} = \boldsymbol{S}\boldsymbol{y}$$

$$\boldsymbol{S} = \boldsymbol{S}_l + (\boldsymbol{I} - \boldsymbol{S}_l)\boldsymbol{X}_g\left[\boldsymbol{X}_g^T(\boldsymbol{I} - \boldsymbol{S}_l)^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{S}_l)\boldsymbol{X}_g\right]^{-1}\boldsymbol{X}_g^T(\boldsymbol{I} - \boldsymbol{S}_l)^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{S}_l)$$

6. Detect outliers on the remainder using boxplot.
7. RMGTWR analysis with M-estimators for each location and each time.

a. Calculating the residual value $\varepsilon_i = (I - S)y$
b. Calculating value $\hat{\sigma}$ and ε_i^*.

$$\hat{\sigma} = \frac{median|\varepsilon_i - median(\varepsilon_i)|}{0.6745}$$

$$\varepsilon_i^* = \frac{\varepsilon_i}{\hat{\sigma}}$$

c. Calculate the weight value of b_i by using the Tukey weighting function.

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

d. Calculates the parameter estimator that has been weighted by the Tukey weighting function

$$\hat{\beta}_g = \left[X_g^T(I - S_l)^T\boldsymbol{B}_i(I - S_l)X_g\right]^{-1}X_g^T(I - S_l)^T\boldsymbol{B}_i(I - S_l)y_i$$

$$\hat{\beta}_l(u_i, v_i, t_i) = [X_l^T\boldsymbol{B}_iX_l]^{-1}\, X_l^T\boldsymbol{B}_i\left(y_i - X_g\hat{\beta}_g\right)$$

e. Repeat steps (a) to (d) until a convergent $\widehat{\boldsymbol{\beta}}_g^m$ and $\widehat{\boldsymbol{\beta}}_l(u_i, v_i, t_i)^m$ are obtained.

8. Partial testing of each RMGTWR parameter on global and local variables [8].
9. Testing the goodness of the GTWR, MGTWR, and RMGTWR models based on the AIC and pseudoR^2.
10. Do the comparison of the results of the MGTWR and RMGTWR models.

3. Result and Discussion

3.1. Data Exploration

According to BPS-Statistics of Indonesia, poverty is seen as an inability on the economic side to meet basic food and non-food needs as measured by expenditure. One of the ways to describe poverty conditions in one region is the percentage of poor people. The percentage of poor population in regency/municipality in Java for the period 2012-2018 is presented on the distribution map in Figure 1.

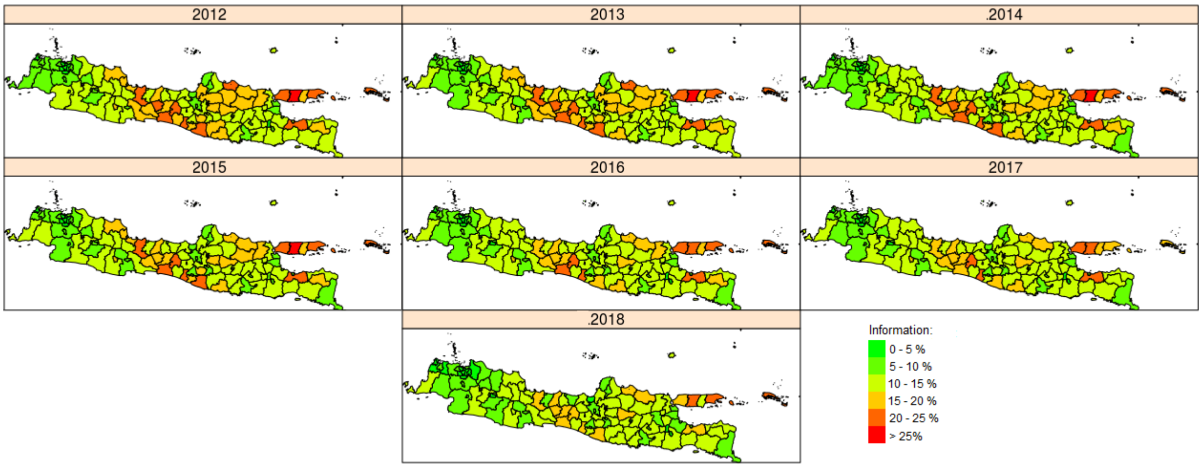

Figure 1: Map of the distribution of the percentage of poor people in Java

Figure 1 shows that the percentage of poor people varies between regency/municipality each year. When compared with Indonesia's poor population of 25.14 million people or 9.41 percent of the total population [14], the provinces of DKI Jakarta and Jawa Barat have a percentage of poor population below the percentage of Indonesia, while some regency/municipality in Jawa Tengah, Jawa Timur, and DI Yogyakarta has a percentage of poor people above 15%. Generally, the percentage of poor people has decreased from 2012-2018, this can be seen by decreasing the red area on the map. The linear relationship between each explanatory variable and the response variable can be seen using the Pearson correlation value, that shows most of each explanatory variable to the percentage value of the poor population has a strong correlation value that is close to 1 and -1. Variable gross regional domestic product (X_1), literacy rate (X_3), percentage of population by age group 15-64 (X_6), expected years of schooling (X_7), and mean years of schooling (X_8) have a negative correlation value, which means an increase in these variables will be followed by a decrease in the percentage of the poor population. Whereas correlation values of the percentage of the population with education completed elementary school (X_2), the percentage of expenditure per capita for food (X_4), and the percentage of households that have purchased Raskin (X_5) is positive, it means an increase in the values will also be followed by an increase in the percentage of poor people in the regency/municipality on Java island. Then multicollinearity is checked from the value of VIF (Variance Inflation Factor). Multicollinearity occurs if the VIF value is greater than ten (VIF> 10). The test results showed that in 2012-2018 most explanatory variables had a VIF value of less than ten, therefore it can be concluded that there is no multicollinearity between variables.

3.2. Robust Mixed Geographically and Temporally Weighted Regression (RMGTWR)

Assumption Test

Testing to determine heterogeneity in data due to spatial influence is done through a variety of homogeneity tests with the Breusch Pagan test for each year from 2012 to 2018 and simultaneously on 118 regency/municipality is presented in Table 2.

Table 2: Test statistics of the Pagan Breusch

Years	P-value
2012	4.60×10^{-5}*
2013	6.44×10^{-2}**
2014	1.28×10^{-2}*
2015	4.68×10^{-2}*
2016	8.53×10^{-2}**
2017	3.26×10^{-1}
2018	3.31×10^{-1}
2012-2018	2.86×10^{-9}*

*significant at $\alpha = 5\%$

**significant at $\alpha = 10\%$

The results of the Breusch Pagan test shown in Table 2 show the majority of observations from 2012 to 2016 and simultaneously obtained p-values less than the real level so that it can be concluded that there is a spatial diversity of the percentage of poor people in each regency/municipality on Java Island. The existence of spatial heterogeneity at various times can be handled by applying temporal weighted regression.

Mixed Geographically and Temporally Weighted Regression Model (MGTWR)

In the MGTWR model, there is a mixture of variables that are global and local together. The determination of global and local variables is based on the percentage of GTWR model parameter estimators that enter the confidence interval of parameters from the global regression model. If the percentage of estimators of GTWR model parameters in a variable is more than 70%, which is included in the global regression confidence interval, the variables are grouped into global variables. Whereas if it is less than 70%, it is grouped into local variables. These results are presented in Table 3.

Table 3: Interval confidence parameters of global regression

Variable	Interval confidence			Parameter Estimator (%)	Information
X_1	-0.32	$< \beta_1 <$	0.02	96.85	Global
X_2	-0.09	$< \beta_2 <$	-0.02	32.93	Local
X_3	-1.35	$< \beta_3 <$	-0.03	77.36	Global
X_4	-0.44	$< \beta_4 <$	0.39	62.11	Local
X_5	2.72×10^{-3}	$< \beta_5 <$	4.92×10^{-3}	59.08	Local
X_6	-0.99	$< \beta_6 <$	0.29	49.15	Local
X_7	3.07	$< \beta_7 <$	5.37	80.75	Global
X_8	-0.28	$< \beta_8 <$	-0.20	48.91	Local

Based on Table 3, shows that the variables X_1, X_3, and X_7 are global variables. While the variables X_2, X_4, X_5, X_6, and X_8 are local variables. The presence of global and local variables is handled using the MGTWR model. MGTWR modeling is done using the Bisquare kernel function selected based on the smallest cross-validation (CV) value. Based on the kernel function, the temporal-spatial ratio (τ) value is 0.019, the spatial distance parameter (λ) is 0.993, the temporal distance parameter (μ) is 0.019, and the temporal-spatial window width value (h_{ST}) is 4,625. The variables in the MGTWR model for global ones have the same parameter estimators for each location and time. While local variables have different parameter estimators for each location and each time. After obtaining the MGTWR model, outliers are detected, one of which is to use the boxplot in Figure 2.

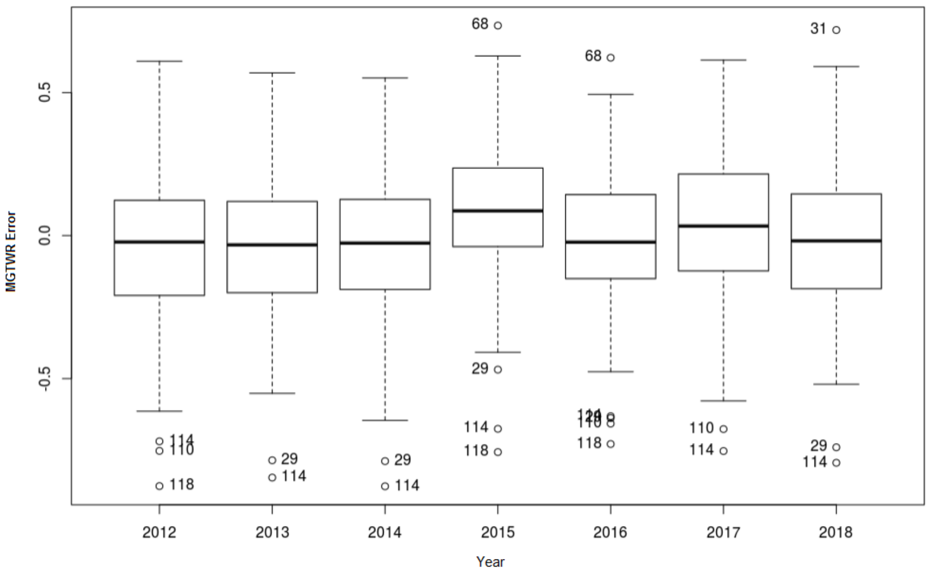

Figure 2: Boxplot of MGTWR model error

Information: 29=Depok City; 31=Tasikmalaya City, 68=Kulon Progo Regency, 110=Batu City, 114=Serang Regency, 118=Tanggerang Selatan City

In the boxplot, it is seen that MGTWR modeling produces several errors that are indicated as outliers. In 2015, 2016, and 2018 there were upper and lower outliers, while lower outliers existed every year. Outliers were mostly found in 2015 and 2016. Therefore, errors that were suspected of being outliers were handled using the RMGTWR model.

Robust Mixed Geographically and Temporally Weighted Regression Model

The estimators of the RMGTWR model parameters are the same as the MGTWR model consisting of global and local variables obtained by the iteration process. Estimation with iteration is carried out until a convergent value is obtained using the M-estimator, the model with a convergent value is obtained at the 3rd iteration. The global parameters of the RMGTWR model have the same values for each location and each year, with $\hat{\beta}_1$ or GRDP of -0.03 and $\hat{\beta}_3$ or literacy rate of -0.63, and $\hat{\beta}_7$ or expected years of schooling of -0.07 are parameter estimator that is negative, meaning that each unit increases in one variable's value while the other variables are fixed then the percentage of poor people in Java will decrease. Meanwhile, local parameters give different effects on each location and time, presented in the line grid diagram in Figure 3.

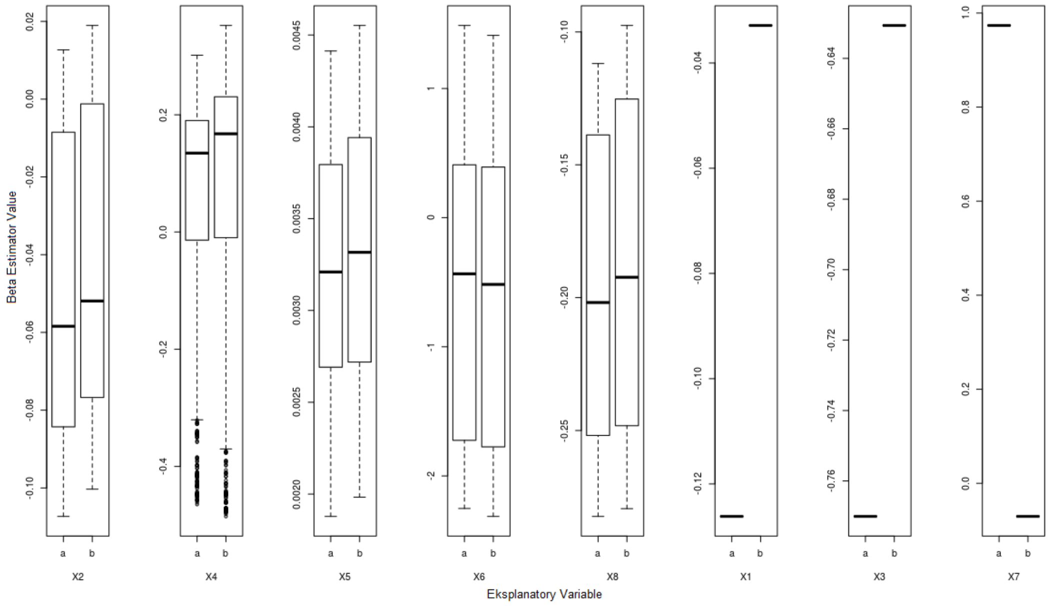

Figure 3: Boxplot of the beta parameter estimator MGTWR models (a) and RMGTWR models (b)

Based on Figure 3, if we compare the beta estimators of the MGTWR model and the RMGTWR model, the local parameters tend to be not significantly different. However, there is a parameter estimator that has changed, that is the $\hat{\beta}_7$ parameter, which previously on the MGTWR model is positive, changes to negative. This is relevant to what is expected that expected years of schooling factor has a negative influence, meaning that each additional one unit of expected years of schooling will reduce the percentage of poor people. Furthermore, the suitability testing of the RMGTWR model is carried out by performing the F test.

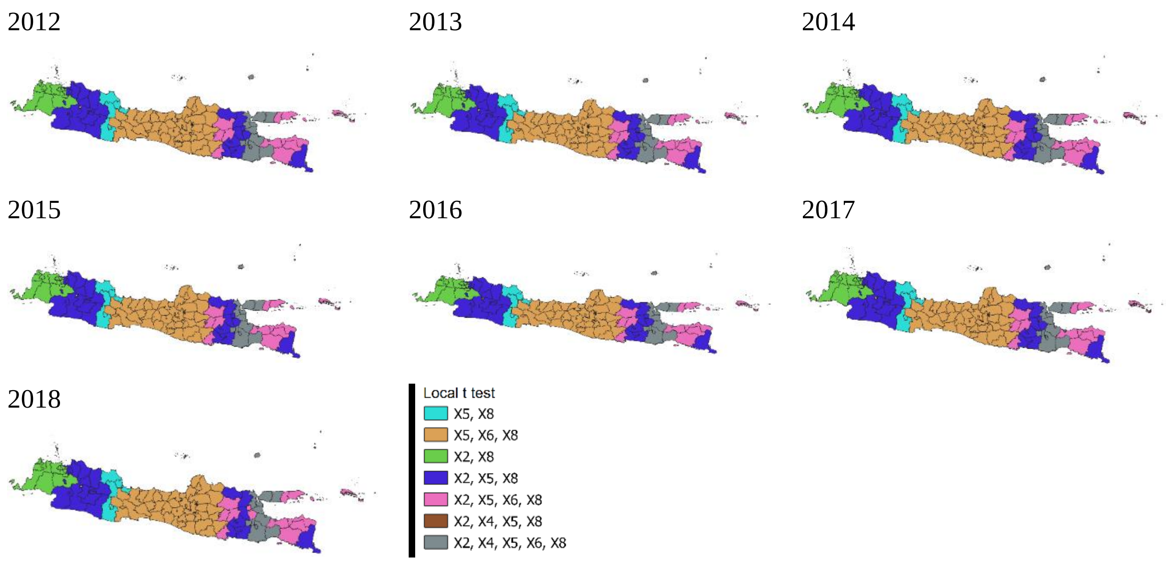

Figure 4: Map of the distribution of partial tests of significant local parameters of the RMGTWR model

The suitability test results of the RMGTWR model using a real level (α) of 5% indicate that the F test statistic value of 74.60 is greater than 0.001, then it is concluded that the RMGTWR model is significantly different from the global regression model. Therefore, the RMGTWR model is better to describe the modeling of the percentage of poor people in regency/municipality in Java or the location and time factors that are very influential in modeling. The partial test of variables is done by t-test for global and local parameters. Based on the results of the global explanatory partial test with a real level (α) of 5%, it can be concluded that only the variable X_3 or literacy rate with at count of -2.17 has a significant effect on the percentage of poor people in Java, while X_1 or GRDP and X_7 or expected years of schooling do not have a significant effect on the percentage of poor people in Java. Partial test results of local variables are presented in the form of distribution maps in Figure 4.

Based on the results of local explanatory partial tests, each location can have different influencing factors. These factors that affect simultaneously, if grouped will form 7 groups of locations. Figure 4 shows that no change and diversity is too large each year, from 2012 to 2017 the group is in the same location, but in 2018 Mojokerto regency has an additional factor of a percentage of the population according to age group 15-64. Groups that form, if grouped by location with the same influencing factors will form several regional groups in Figure 5.

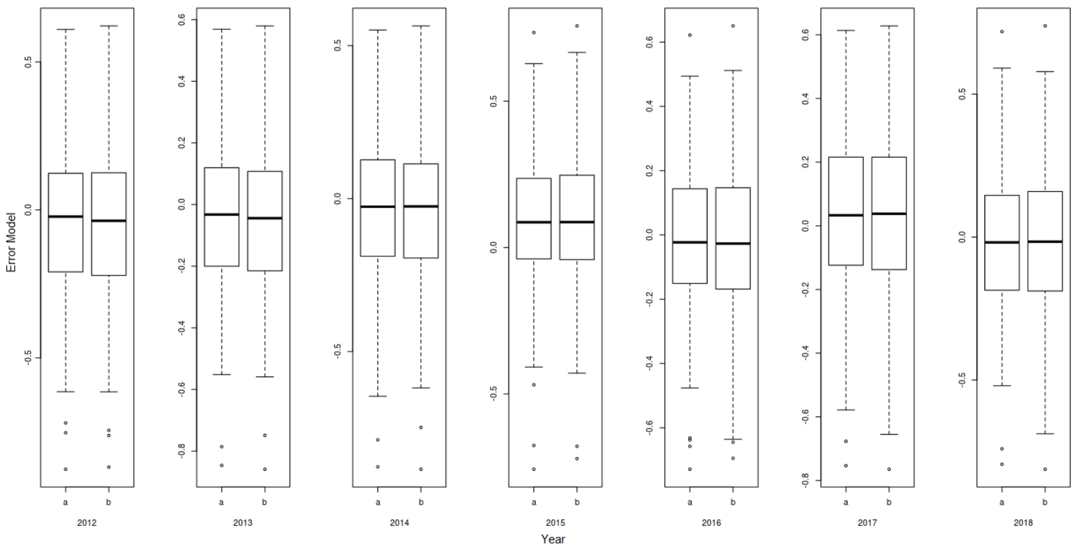

Figure 5: Boxplot of the error MGTWR models (a) and RMGTWR models (b)

Figure 5 shows that after the RMGTWR model was formed, the model still has outliers. But the RMGTWR model makes the error distance wider. From 2015 to 2018 some lower outliers were reduced, namely Depok City, while other outliers were the same regency/municipality. Since the beginning, the MGTWR model has a slight error, which is only around 2.4% of the total data. However, the RMGTWR model can be said to be a good model because it can reduce 20% of the MGTWR model errors. Then a comparison of the goodness of the model is performed on the global regression model, GTWR, MGTWR, and RMGTWR to see which model is better for modeling the percentage of poor people in Java from 2012-2018. The criteria used is to compare the values of pseudoR^2 and AIC as in Table 4.

Table 4: Comparison of model goodness

	GTWR	MGTWR	RMGTWR
pseudoR^2	0.6921	0.7292	0.7273
AIC	252.985	198.753	202.802

Based on the results of a summary of the goodness of the model in Table 4 it was found that the MGTWR model has the highest value of pseudoR^2 72.92% and the smallest AIC is 198.7532. Whereas for the RMGTWR model the M-estimator produces a pseudoR^2 value smaller than 0.28% compared to the MGTWR model, this is in line with the summary results of the MGTWR error and RMGTWR error in Figure 5 that the change in error outliers does not have a significant impact because the outliers in the MGTWR model are not too numerous. Therefore, the RMGTWR model can still be said to be the best model in modeling the percentage of poor people in Java from 2012 to 2018 because it can reduce the number of outliers in MGTWR errors and the difference in pseudoR^2 is also not much different.

4. Conclusion

The percentage of poor people has spatial and time diversity so that modeling can be done with GTWR. Besides, global variables and local variables can be clearly distinguished so that they can use MGTWR. In MGTWR modeling, we found outliers in errors that affect parameter estimators. Outliers are handled using the M-estimator RMGTWR, this can reduce some of the outliers. Even though the pseudoR^2 RMGTWR value is not better than the MGTWR model, it has only a smaller value of 0.28%. Also, using the RMGTWR model can correct the sign on the influence of a factor, the expected years of schooling factor, becoming more relevant. Therefore, the RMGTWR model is the best model for modeling the percentage of poor people in regency/municipality in Java in 2012-2018. The influential factors together form 7 groups, with the groups located at locations close to each other.

5. Recommendations

In further research, other robust estimators can be used, such as the S estimator or the MM estimator for the outliers percentage greater than 10%.

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