Geographically Weighted Regression for Prediction of Underdeveloped Regions in East Java Province Based on Poverty Indicators

Rusdi Hidayat N[1], Bambang Widjanarko Otok[2], Zumarsiyah Mahsyari[2], Siti Halimah Sa'diyah[2], and Dimas Achmad Fadhila[2]

[1]*Business Administration Study Program, FISIP, UPN "Veteran" East Java, Surabaya*
[2]*Department of Statistics, FMKSD, Institut Teknologi Sepuluh Nopember, Surabaya*

Keywords: GWR, Kernel Function, Adaptive Bisquare, Underdeveloped Regions, Poverty.

Abstract: Underdevelopment problem of a region can be seen from the dimensions of the economy, human resources, financial capability, infrastructure, accessibility, and regional characteristics. One method to see a region is underdeveloped or not is by looking the percentage of people living in poverty in a region in the publication data of underdeveloped regional indicators issued by the Central Bureau of Statistics (BPS). The results showed that the percentage of people in East Java Province who are living in poverty using linear regression is not yet appropriate. The percentage of people living in poverty spread spatially because there is heterogeneity between the observation sites which means that the observation of a location depends on the observation in another location with adjacent distance so that the spatial regression modeling was done with Adaptive Bisquare Kernel function. The grouping results with GWR resulted in nine groups based on significant variables. Each group eas characterized by life expectancy, mean years of schooling, expenditure and literacy rate.

1 INTRODUCTION

Underdeveloped regions are an area with districts where communities and their territories are relatively less developed than other regions on a national scale. The backwardness of the area can be measured based on six main criteria: economy, human resources, infrastructure, regional financial capacity, accessibility and regional characteristics (Directorate General of Underdeveloped Regions Development, 2016). To identify whether a district is underdeveloped can be measured using predetermined standards referring to the Minister of Village Regulations, Development of Underdeveloped Regions and Transmigration No. 3 of 2016 on Technical Guidelines for the Determination of Indicators of Underdeveloped Regions Nationally. The purpose of this paper is to identify the problem of backwardness of a region based on the percentage of poor people indicator.

If a study is influenced by the spatial aspect, then it is necessary to consider spatial data on the model. Spatial data is data that contains location information. In spatial data, frequent observations at a site depends on observation in another adjacent location (neighboring) (Anselin, 1988). The law is the basis for reviewing problems based on the effects of location or spatial methods. In modeling, if the classical regression model is used as an analytical tool on spatial data, it can lead to inaccurate conclusions because the assumption of error is mutually free and the assumption of homogeneity is not met.

2 LITERATURE RIVIEW

Geographically Weighted Regression (GWR) model is the development of a regression model where each parameter is calculated at each observation location, so that each location of observation has different regression parameter values. The GWR model is an expansion of the global regression model in which the basic idea is derived from non-parametric regression (May, 2006). The y response variable in the GWR model is predicted by the predictor

Hidayat N, R., Otok, B., Mahsyari, Z., SaâĂŹdiyah, S. and Fadhila, D.
Geographically Weighted Regression for Prediction of Underdeveloped Regions in East Java Province Based on Poverty Indicators.
DOI: 10.5220/0007553708980907
In *Proceedings of the 2nd International Conference Postgraduate School (ICPS 2018)*, pages 898-907
ISBN: 978-989-758-348-3

variable and each regression coefficient depends on the location where the data is observed. The GWR model is stated as follows (Fotheringham et al., 2002):

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

Estimation of GWR model parameters is done by Weighted Least Squares (WLS) method through assigning different weights to each location where data is observed. Suppose weighting for each location (u_i,v_i) is $w_j(u_i,v_i)$, j = 1, 2,…,n then the parameters at the observation location (u_i,v_i) then the parameters at the observation location $w_j(u_i,v_i)$ in equation (1) and then minimize the sum of residual squares, or in the matrix form the sum of the residual squares is:

$$\begin{aligned}\boldsymbol{\varepsilon}^T\mathbf{W}(u_i,v_i)\boldsymbol{\varepsilon} &= \mathbf{y}^T\mathbf{W}(u_i,v_i)\mathbf{y} - 2\boldsymbol{\beta}^T(u_i,v_i)\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{y}\\ &\quad + \boldsymbol{\beta}^T(u_i,v_i)\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{X}\boldsymbol{\beta}(u_i,v_i)\end{aligned} \qquad (2)$$

with:

$$\boldsymbol{\beta}(u_i,v_i) = \begin{pmatrix}\beta_0(u_i,v_i)\\ \beta_1(u_i,v_i)\\ \vdots \\ \beta_p(u_i,v_i)\end{pmatrix} \text{ and}$$

$$\mathbf{W}(u_i,v_i) = \operatorname{diag}\left(w_1(u_i,v_i), w_2(u_i,v_i), \cdots, w_n(u_i,v_i)\right)$$

If equation (2) is lowered to $\boldsymbol{\beta}^T(u_i,v_i)$ and the result is equal to zero then obtained parameter estimator GWR model:

$$\hat{\boldsymbol{\beta}}(u_i,v_i) = \left[\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{y} \qquad (3)$$

For instance $\mathbf{x}_i^T = (1, x_{i1}, x_{i2}, \cdots, x_{ip})$ is the i row element of the X matrix. Then the prediction value for y at the observation location (u_i,v_i) can be obtained in the following way:

$$\hat{y}_i = \mathbf{x}_i^T\hat{\boldsymbol{\beta}}(u_i,v_i) = \mathbf{x}_i^T\left(\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{y}$$

So for all observations can be written as follows:

$\hat{\mathbf{y}} = (\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n)^T = \mathbf{L}\mathbf{y}$ and

$\hat{\boldsymbol{\varepsilon}} = (\hat{\varepsilon}_1, \hat{\varepsilon}_2, \cdots, \hat{\varepsilon}_n)^T = (\mathbf{I} - \mathbf{L})\mathbf{y}$

with **I** is an identity matrix of *nxn* and

$$\mathbf{L} = \begin{pmatrix}\mathbf{x}_1^T\left(\mathbf{X}^T\mathbf{W}(u_1,v_1)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_1,v_1)\\ \mathbf{x}_2^T\left(\mathbf{X}^T\mathbf{W}(u_2,v_2)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_2,v_2)\\ \vdots \\ \mathbf{x}_n^T\left(\mathbf{X}^T\mathbf{W}(u_n,v_n)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_n,v_n)\end{pmatrix} \qquad (4)$$

The weighting role of the GWR model is important because this weighted value represents the location of the observed data with each other. The weighting scheme on GWR can use several different methods. There is some literature that can be used to determine the weighting for each different location on the GWR model, such as by using Kernel Function.

The Kernel Function is used to estimate the parameters in the GWR model if the distance function (w_j) is a continuous and monotonous function down (Chasco, Garcia and Vicens, 2007). Weights that are formed by using this kernel function are the Gaussian Distance Function, Exponential Function, Bisquare Function, and Tricube Kernel Function and involve the smoothing parameter (Lesage, 2001). Cross Validation (CV) method to select the optimum bandwidth, which is mathematically defined as follows:

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

with $\hat{y}_{\neq i}(h)$ is the value of the appraiser y_i where the observations are on location (u_i,v_i) removed from the estimation process. To get the value h the optimal is then obtained from h which results in a minimum CV value.

Hypothesis testing on the GWR model consists of testing the suitability of the GWR model and testing the model parameters. Testing the suitability of the GWR model (goodness of fit) is done with the following hypothesis:

$H_0 : \beta_k(u_i,v_i) = \beta_k$ (there is no significant difference between global regression model and GWR)

H_1 : At least, there is one $\beta_k(u_i,v_i) \neq \beta_k$ for each $k = 0, 1, 2, \cdots, p,$ and $i = 1, 2, \cdots, n$ (there is a significant difference between the global regression model and GWR).

Determination of test statistics based on Residual Sum of Square (RSS) obtained respectively below

H_0 dan H_1. Under conditions H_0, using OLS method obtained the following RSS value:

$\mathrm{RSS}(\mathrm{H}_0) = \hat{\boldsymbol{\varepsilon}}^T\hat{\boldsymbol{\varepsilon}} = (\mathbf{y}-\hat{\mathbf{y}})^T(\mathbf{y}-\hat{\mathbf{y}}) = \mathbf{y}^T(\mathbf{I}-\mathbf{H})\mathbf{y}$ with $\mathbf{H} = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ which is idempotent. Under conditions H_1, spatially varying regression coefficients in equation (1) is determined by the GWR method, to obtain the following RSS values:

$$\begin{aligned}\mathrm{RSS}(\mathrm{H}_1) &= \hat{\boldsymbol{\varepsilon}}^T\hat{\boldsymbol{\varepsilon}} = (\mathbf{y}-\hat{\mathbf{y}})^T(\mathbf{y}-\hat{\mathbf{y}}) \\ &= \mathbf{y}^T(\mathbf{I}-\mathbf{L})^T(\mathbf{I}-\mathbf{L})\mathbf{y}\end{aligned} \tag{5}$$

so obtained the following test statistic (Leung et al., 2000a):

$$F_1 = \frac{RSS(\mathrm{H}_1)\Big/\left(\dfrac{\delta_1^2}{\delta_2}\right)}{RSS(\mathrm{H}_0)/(n-p-1)}$$

Below H_0 , F_1 will follow the F distribution with degrees of freedom $df_1 = \left(\dfrac{\delta_1^2}{\delta_2}\right)$ and $df_2 = (n-p-1)$. If taken the level of significance α then reject H_0 if $F_1 < F_{1-\alpha,df_1,df_2}$.

with:

$$\delta_i = tr\left(\left[(\mathbf{I}-\mathbf{L})^T(\mathbf{I}-\mathbf{L})\right]^i\right),\ i=1,2\,. \tag{6}$$

Another alternative as a test statistic is to use the difference in the number of residual squares below H_0 and below H_1 (Leung et al., 2000a), i.e:

$$\begin{aligned}F_2 &= \frac{\left(RSS(H_0)-RSS(H_1)\right)/\tau_1}{RSS(H_1)/\delta_1} \\ &= \frac{\mathbf{y}^T\left[(\mathbf{I}-\mathbf{H})-(\mathbf{I}-\mathbf{L})^T(\mathbf{I}-\mathbf{L})\right]\mathbf{y}/\tau_1}{\mathbf{y}^T(\mathbf{I}-\mathbf{L})^T(\mathbf{I}-\mathbf{L})\mathbf{y}/\delta_1}\end{aligned}$$

Below H_0 F_2 will follow the distribution F with degrees of freedom $df_1 = \dfrac{\tau_1^2}{\tau_2}$ and $df_2 = \left(\dfrac{\delta_1^2}{\delta_2}\right)$. If taken the level of significance α then reject H_0 if $F_2 \geq F_{\alpha,df_1,df_2}$.

with:

$$\tau_i = tr\left(\left[(\mathbf{I}-\mathbf{H})-(\mathbf{I}-\mathbf{L})^T(\mathbf{I}-\mathbf{L})\right]^i\right),\ i=1,2$$

If it is concluded that the GWR model is significantly different from the global regression model, then the next step is to perform a partial test to find out whether there is a significant influence difference from the predictor variable x_k between one location and another (May, He and Fang, 2004). This test can be done by hypothesis:

H_0 : $\beta_k(u_1,v_1) = \beta_k(u_2,v_2) = \cdots = \beta_k(u_n,v_n)$ (there is no significant difference of influence from the predictor variable x_k between one location and another)

H_1 : At least, there is one, $\beta_k(u_i,v_i)$, for $i=1,2,...,n$ $(k=0,1,2,\cdots,p)$ which different. (there is a significant effect difference from the predictor variable x_k between one location and another location).

To perform the above test it is determined first variance $\hat{\beta}_k(u_i,v_i)$ (i = 1, 2, ..., n) which denoted by:

$$\begin{aligned}V_k^2 &= \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\beta}_k(u_i,v_i) - \frac{1}{n}\sum_{i=1}^{n}\hat{\beta}_k(u_i,v_i)\right)^2 \\ &= \frac{1}{n}\boldsymbol{\beta}_k^T\left[\mathbf{I}-\frac{1}{n}\mathbf{J}\right]\boldsymbol{\beta}_k\end{aligned}$$

with $\boldsymbol{\beta}_k(u_i,v_i) = \begin{pmatrix}\beta_k(u_1,v_1)\\ \beta_k(u_2,v_2)\\ \vdots\\ \beta_k(u_n,v_n)\end{pmatrix}$.

While the test statistic used is:

$$F_3 = \frac{V_k^2\Big/tr\left(\dfrac{1}{n}\mathbf{B}_k^T\left[\mathbf{I}-\dfrac{1}{n}\mathbf{J}\right]\mathbf{B}_k\right)}{\mathrm{RSS}(\mathrm{H}_1)/\delta_1}$$

with:

$$\mathbf{B}_k = \begin{pmatrix}\mathbf{e}_k^T\left[\mathbf{X}^T\mathbf{W}(u_1,v_1)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_1,v_1)\\ \mathbf{e}_k^T\left[\mathbf{X}^T\mathbf{W}(u_2,v_2)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_2,v_2)\\ \vdots\\ \mathbf{e}_k^T\left[\mathbf{X}^T\mathbf{W}(u_n,v_n)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_n,v_n)\end{pmatrix},$$

$\mathbf{e}_k$ is column vector which is size $(p+1)$ which is worth one for the k elements for the other. Matrix **L** as in (4) and RSS (H_1) as in the equation (5).

Below H_0, test statistic F_3 will be distributed F with degrees of freedom $df_1 = \left(\frac{\gamma_1^2}{\gamma_2}\right)$ and $df_2 = \left(\frac{\delta_1^2}{\delta_2}\right)$ with $\gamma_i = tr\left(\frac{1}{n}\mathbf{B}_k^T\left[\mathbf{I}-\frac{1}{n}\mathbf{J}\right]\mathbf{B}_k\right)^i$ *i=1,2* dan δ_i as in equation (6). Reject H_0 if $F_3 \geq F_{\alpha,df_1,df_2}$ (Leung et al., 2000a).

The testing of the significance of model parameters at each location is done by partially testing the parameters. This test is conducted to determine which parameters significantly affect the response variable. The form of the hypothesis is as follows:

$H_0 : \beta_k(u_i, v_i) = 0$

$H_1 : \beta_k(u_i, v_i) \neq 0$ with $k = 1, 2, \cdots, p$

The parameter estimator $\hat{\boldsymbol{\beta}}(u_i, v_i)$ will follow the normal multivariate distribution with the average $\beta(u_i, v_i)$ and the covariance variant matrix $\mathbf{C}_i\mathbf{C}_i^T\sigma^2$, with: $\mathbf{C}_i = \left(\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_i,v_i)$, so it get to:

$$\frac{\hat{\beta}_k(u_i,v_i)-\beta_k(u_i,v_i)}{\sigma\sqrt{c_{kk}}} \sim \mathrm{N}(0,1)$$

with c_{kk} is the k-diagonal element of the matrix $\mathbf{C}_i\mathbf{C}_i^T$. So the test statistic used is:

$$T_{hit} = \frac{\hat{\beta}_k(u_i,v_i)}{\hat{\sigma}\sqrt{c_{kk}}}$$

Below H_0 T will follow the t distribution with degrees of freedom $\left(\frac{\delta_1^2}{\delta_2}\right)$ while $\hat{\sigma}$ is acquired by rooting $\hat{\sigma}^2 = \frac{\mathrm{RSS}(\mathrm{H}_1)}{\delta_1}$. If the given level of significance is α, then the decision to decline H_0 or in other words parameters $\beta_k(u_i, v_i)$ significant to the if model $|T_{hit}| > t_{\alpha/2, df}$, where $df = \left(\frac{\delta_1^2}{\delta_2}\right)$.

Akaike Information Criterion Correction (AICc) method used to select the best model defined as follows :

$$AIC_c = 2n\ln(\hat{\sigma}) + n\ln(2\pi) + n\left\{\frac{n+tr(\mathbf{S})}{n-2-tr(\mathbf{S})}\right\} \quad (7)$$

with :

$\hat{\sigma}$: The standard deviation estimator value of the maximum likelihood estimated error, ie $\hat{\sigma}^2 = \frac{RSS}{n}$

S : Where projection matrix $\hat{\mathbf{y}} = \mathbf{S}\mathbf{y}$

The best model selection is done by determining the model with the smallest AICc value (Fotheringham et al., 2002).

3 METHODOLOGY

This study used secondary data from Publication of BPS in 2014. The research variables are presented in Table 1 below.

Table 1: Research variable.

Variable	Indicator
Y	Percentage of poor people
X1	Life expectancy
X2	Average school duration
X3	Per capita population expenditure
X4	Literacy

Stages performed in the study.

1. Description of characteristics and pattern of percentage distribution of poor people in East Java.
2. Modeling percentage of poor people in East Java with Linear Regression and GWR with AIC criteria. The steps are as follows.
   i. Detection of muticolinearity cases.
   ii. Modeling percentage of poor people in East Java with Linear Regression:
      a. Calculates the parameter estimator value of the Linear regression model
      b. Perform parallery testing simultaneously and partially.
      c. Testing the residual assumption of IIDN.
   iii. Model GWR on the percentage of the poor in East Java:
      a. Calculate euclidian distance between observation locations based on geographical position. Euclidean distance between location *i* located at coordinate (u_i, v_i) to location *j* at coordinate (u_j,v_j)

b. Determine the optimum bandwidth with CV criteria
c. Determine the optimum weighting with the gauss kernel weighted function.
d. Calculates the value of the GWR model parameter estimator
e. Testing GWR parameters (partial test and partial test)

Comparing the AICc value of the Global / Linear Regression Model with the GWR model, the minimum AICc value is the best model.

4 RESULT AND DISCUSSION

The description of this study includes the mean and standard deviation of each variable which is presented in Table 2.

Table 2: Description of research variables.

Variable	Minimum	Maximum	Mean	StDev
Y	4.59	25.8	12.1	4.99
X1	62.16	73.3	69.2	3.15
X2	3.49	10.9	7.3	1.72
X3	7143	15492	10013	2062
X4	77.93	98.5	92.3	4.84

4.1 Multicolinearity Detection

One of the requirements in regression analysis with some predictor variables is that there is no case of multicollinearity or there is no predictor variable that has correlation with other predictor variables. The detection of muticollinearity is based on the Variance Inflation Factor (VIF) value. Here is the VIF value of each predictor variable.

Table 3: VIF of predictor variable.

Variabel	X1	X2	X3	X4
VIF	2.085	9.066	4.698	4.526

Table 3 shows that all predictor variables have a VIF value of less than 10. This detects that there are no multicollinearity cases or no predictor variables that have correlation with other predictor variables.

4.2 Significance Test of Linear Regression of Hypertension Prevalence

Here is the test of the significance of linear regression parameters either simultaneously or partially to determine the effect of predictor variables used. The hypothesis for simultaneous parameter significance test in linear regression is as follows.

H_0 : $\beta_1 = \beta_2 = \ldots = \beta_4 = 0$ (parameters have no significant effect on the mode)

H_1 : At least, there is one $\beta_k \neq 0$; $k = 1, 2, \ldots, 4$ (at least, there is one parameter that significantly affects the model)

Table 4: ANOVA linear regression table.

Variation Sources	Sum of Squares	df	Mean Square	F	P
Regression	598.32	9	66.48	2.14	0.030
Residual	4418.32	142	31.11		
Total	5016.64	151			

Table 4 yields a value F_{count} in the amount of 2,14 and p-value in the amount of 0,030. Based on the level of significance (α) in the amount of 5% and $F_{(0,05;9;142)}$ in the amount of 1,946, obtained decision reject H_0 because of value $F_{count} > F_{(0,05;9;142)}$ or P-Value < 0,05. This can be interpreted that there is at least one parameter that has a significant effect on the prevalence of hypertension.

Furthermore, to determine which predictor variables that give a significant influence, then the partial significance of the parameters were tested and presented in Table 5. The following hypothesis test of spatial parameter significance of linear regression model (global).

$H_0 : \beta_k = 0$,

$H_1 : \beta_k \neq 0$, $k = 1,2,3,4$

Table 5. Parameter test of partial regression coefficients.

Parameter	Coefficient	SE Coefficient	T	Sig.
β0	59.720	16.410	3.640	0.001
β1	0.076	0.187	0.410	0.687
β2	-1.422	0.789	-1.800	0.081
β3	-0.000	0.000	-0.140	0.891
β4	-0.454	0.179	-2.530	0.016

Based on the test results in Table 5, with a significant level (α) in the amount of 5% and $t_{(\alpha/2;n-p-1)} = t_{(0.025,33)} = 2.035$, it is obtained that all values of T smaller than $t_{(0.025,33)}$, except parameters β_4 . This shows that the literacy rate variable significantly affects the percentage of poor people.

4.3 Testing Residual Assumptions

Testing of residual assumptions is identical, independent, and normally distributed.

4.3.1 Identical Residual Assumption Test

One assumption test in OLS regression is that residual variance should be homoscedasticity (identical) or case of heteroscedasticity. How to identify the case of heteroscedasticity is to create a regression model between residual and predictor variables. If there are predictor variables that significantly affect the model, then it can be said that the residual is not identical or happened case of heteroscedasticity. Testing identical residual assumptions provides information that no cases of heteroscedasticity or residual have been identical to a significant level (α) of 0.05 and $F_{(\alpha;p,n-p-1)} = F_{(0,05;4,33)} = 2.659$. This is because of the P-Value (0.119) is bigger than α (0.05) and F (1.99) is smaller than 2.659, then there is no heteroscedasticity.

4.3.2 Independent Residual Assumption Test

An independent residual assumption test is used to determine whether or not the relationship exists between residuals. The test statistic used is Durbin-Watson. The value of DW = 1.099 earned value $d = 2{,}07875$ with $d_L = 1{,}0201$ and $d_U = 1{,}9198$. So the decision that can be taken is Reject H0 because $d_U = 1{,}9198 < d < (4 - d_U) = 2{,}0802$. It shows that there is a residual relationship, so that the independent residual assumption is not met.

4.3.3 Normal Distributed Assumption Test

Normal distributed assumption test is performed by the following Kolmogorov-Smirnov test.
H_0 : Data is normally distributed
H_1 : Data is not normally distributed

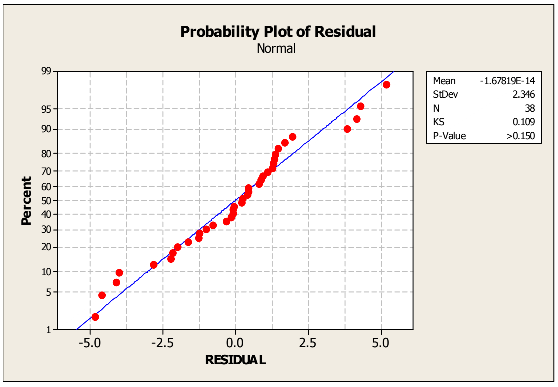

Figure 1. Probability plot normal residual.

Based on Figure 1, it is found that the red dots spread close to the linear (normal) line meaning that the data has been normally distributed. In addition, it can also be seen from the value of P-Value is greater 0,15. So the decision that can be taken is Failed Reject H_0 at a significant level (α) in the amount of 5%, that is, the data has fulfilled normal distributed assumptions. Based on the results of the assumption test, it can be concluded that the residuals in the linear regression model (global) data have normal distribution, but the identical and independent assumptions are not met. So that spatial regression is done with GWR approach.

4.4 Modeling of Spatial Regression of Percentage of Poor People

Analysis using GWR method aims to determine the variables that affect the percentage of poor people in each location of observation that is the district / city in the province of East Java. The first step to get the GWR model is to determine the point of latitude and longitude coordinates at each location, calculate the euclidean distance and determine the optimum bandwidth value based on Cross Validation (CV) criteria. The next step is to determine the weighting matrix with kernel function: Fixed Gaussian, Fixed Bi-Square, Adaptive Gaussian, Adaptive Bi-Square and estimates GWR model parameters. The weighted matrix obtained for each location is then used to form the model, so that different models are obtained at each observation location.

The hypothesis test of the GWR model consists of two tests, namely the GWR model conformity test and the parameter significance test of the GWR model. Here are the results of hypothesis testing GWR model.

H_0 : $\beta_k(u_i, v_i) = \beta_k$;
(There was no significant difference between the linear regression model (global) and the GWR model)

H_1 : At least, there is one $\beta_k(u_i, v_i) \neq \beta_k$ k = 1, 2, ….,9
(There is a significant difference between the linear regression model (global) and the GWR model)

Table 6. Estimated GWR on kernel function weight.

Statistic	Function weight			
	Fixed Gaussian	Fixed Bi-square	Adaptive Gaussian	Adaptive Bi-square*
MSE	5.560	5.049	5.989	1.995
R^2	0.829	0.852	0.797	0.998
AICc	185.676	184.839	186.017	-14185

Table 6 shows the comparison of estimated GWR models with different weights. The GWR model conformity test is performed by using the difference of sum of residual squares of GWR model and global regression model. The GWR model will be significantly different from the global regression model if it can significantly reduce the number of residual squares. Table 6 shows that the smallest AICc value is the GWR model with the Adaptive Bi-Square kernel function weights, that is -14185. So, by using the level of significance α at 5% it can be concluded that the GWR model is significantly different from the global regression model. This means that the GWR model with the Adaptive Bi-Square kernel function weights more feasible to describe the percentage of poor people in East Java Province.

Next is a test of the significance of GWR model parameters with Adaptive Bi-Square kernel function weights partially to know which parameters significantly influence the percentage of poor people in each location of observation. The grouping of districts with the same variables that significantly affect the percentage of poor people is presented in Table 7.

Table 7. T-count value in variables in each regency / city using adaptive bisquare.

Regency/City	Predictor Variable			
	X1	X2	X3	X4
"Pacitan Regency"	-0.58	0.69	-0.53	-2.89*
"Ponorogo Regency"	0.46	-0.39	0.51	-3.06*
"Trenggalek Regency"	1.22	-0.33	-0.24	-1.69
"Tulungagung Regency"	2.31*	0.35	-0.88	-2.48*
"Blitar Regency"	-1.73	0.92	-2.99*	-0.39
"Kediri Regency"	1.22	-0.07	-0.83	-0.67
"Malang Regency"	1.37	-1.03	-1.41	-0.48
"Lumajang Regency"	2.73*	1.22	-1.53	-2.76*
"Jember Regency"	0.97	0.11	-1.36	-0.60
"Banyuwangi Regency"	-0.44	0.78	-0.74	-2.85*
"Bondowoso Regency"	1.87	-1.50	1.55	-2.46*
"Situbondo Regency"	2.92*	-0.74	1.50	-1.64
"Pasuruan Regency"	-0.01	-0.51	0.32	-1.80
"Probolinggo Regency"	-0.05	0.95	-1.10	-2.97*
"Sidoarjo Regency"	3.02*	-0.92	1.61	-2.00*
"Mojokerto Regency"	0.46	0.10	-0.14	-1.00
"Jombang Regency"	1.36	0.82	-1.17	-0.89
"Nganjuk Regency"	0.55	-0.08	1.05	-1.16
"Madiun Regency"	2.92*	0.67	-1.13	-2.97*
"Magetan Regency"	1.06	-1.16	0.10	-0.61
"Ngawi Regency"	0.50	-3.55*	0.60	1.72
"Bojonegoro Regency"	-2.41*	2.43*	-2.84*	0.38

"Tuban Regency"	1.81	0.35	-0.93	-2.19*
"Lamongan Regency"	-1.80	0.01	0.47	1.48
"Gresik Regency"	3.14*	-5.10*	2.16*	1.99*
"Bangkalan Regency"	-2.10*	0.28	-0.22	-2.63*
"Sampang Regency"	3.37*	-3.91*	3.84*	2.83*
"Pamekasan Regency"	0.01	0.83	-0.90	-3.00*
"Sumenep Regency"	2.90*	1.59	0.13	-2.68*
"Kediri City"	1.54	0.19	-1.43	-0.95
"Blitar City"	-1.15	1.24	-1.36	-1.69
"Malang City"	0.32	0.96	-1.28	-1.56
"Probolinggo City"	2.90*	1.59	0.09	-2.68*
"Pasuruan City"	-0.15	0.92	-1.08	-3.05*
"Mojokerto City"	0.82	-0.09	1.08	-1.13
"Madiun City"	2.20*	-1.33	0.72	-2.00*
"Surabaya City"	-0.69	-4.77*	3.48*	3.41*
"Batu City"	3.22*	-5.15*	2.23*	2.04*

5 CONCLUSIONS

Result of modeling percentage of poor population in East Java Province based on Regency / City using linear regression showed that only one variable that affect the percentage of poor people, which is literacy rate. The percentage of poor people in East Java Province spread spatially because there is heterogeneity between observation locations which means that the observation of a location depends on the observation in other location with adjacent distance so spatial regression modeling with Adaptive Bisquare kernel function was done, which produced 9 groups.

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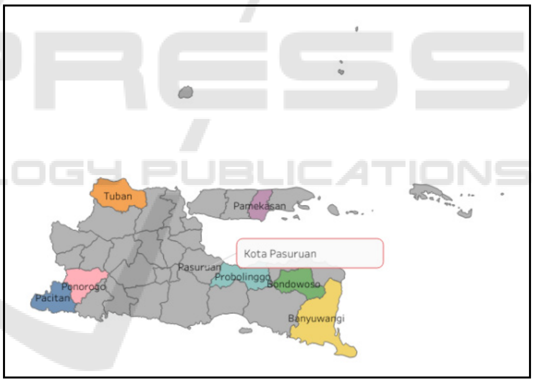
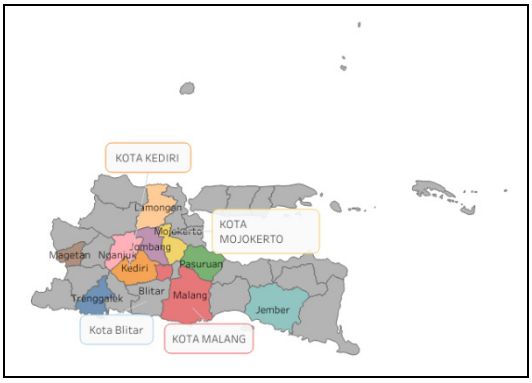
APPENDIX

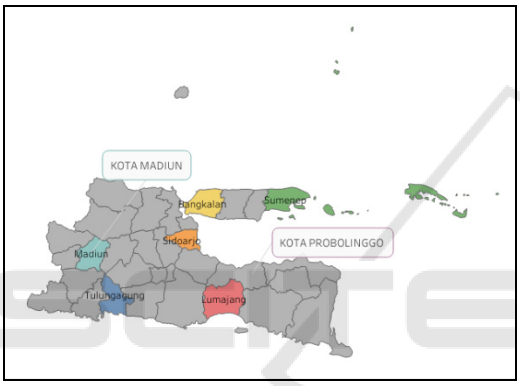
Group 1: Regency / City di in East Java with Percentage of Poor People Not Affected by Literacy Rate



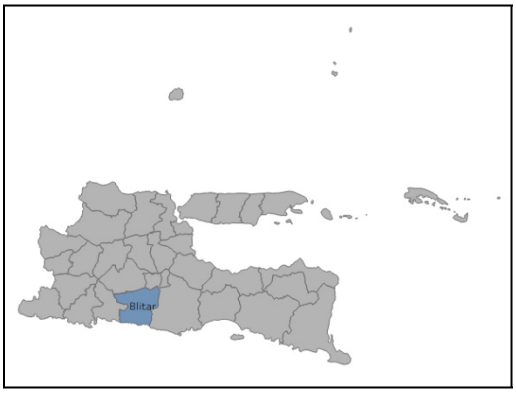
Group 2: Regency / City in East Java with Percentage of Poor People Not Affected by Life Expectancy Factors, Average School Duration, Per Capita Population Expenditure, and Literacy Rate



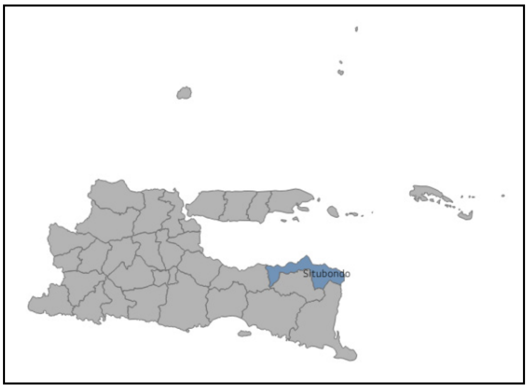
Group 3: Regency / City in East Java with Percentage of Poor People Affected by Life Expectancy Figures and Literacy Rates



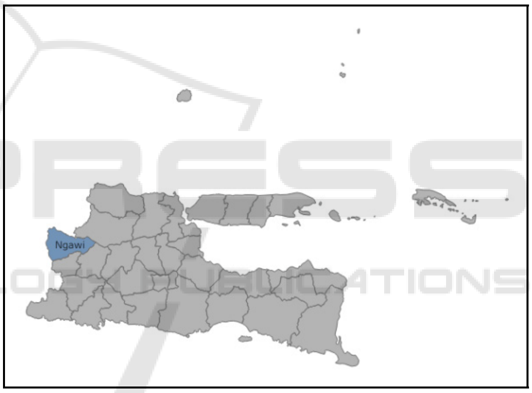
Group 4: Regency / City in East Java with Percentage of Poor People Affected by Capita Population Expenditure



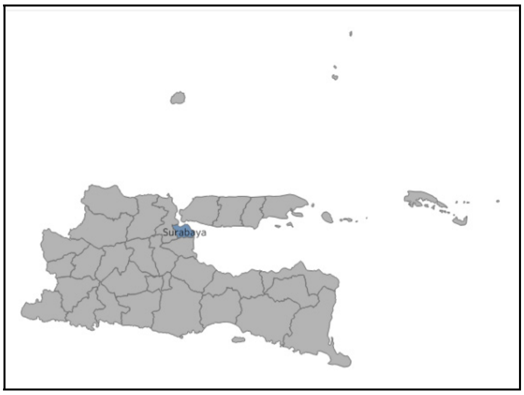
Group 5: Regency / City in East Java with Percentage of Poor People Affected by Life Expectancy Factor



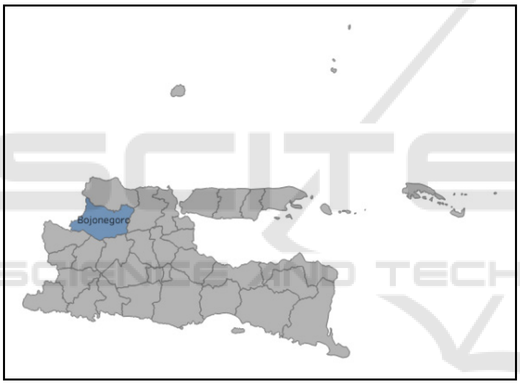
Group 6: Regency / City in East Java with Percentage of Poor People Affected by Average School Duration



Group 7: Regency / City in East Java with Percentage of Poor People Affected by Average School Duration, Per Capita Population Expenditure, and Literacy Rate



Group 8: Regency / City in East Java with Percentage of Poor People Affected by Life Expectancy Factors, Average School Duration, Per Capita Population Expenditure, and Literacy Rate



Group 9: Regency / City in East Java with Percentage of Poor People Affected by Life Expectancy Factors, Average School Duration, and Per Capita Population Expenditure