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Analysis of Factors Affecting the Number of Poor People in Indonesia Using Geographycally Weighted Regression

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ABSTRACT

The GWR model is better at modeling the number of the poor in each province than the global regression model. The variables affecting poverty in Indonesia are the number of population of provinces (X8), percentage of provincial ground floor housing (X12). On the other hand, the variables that are not affecting the poverty in Indonesia for all provinces are the percentage of provincial electricity users (X4) and the percentage of households that can access decent drinking water in the province (X11), the factors that influence the number of poverty between provinces differ depending on the socio-cultural of province.

Keywords: Poverty, Global Regression, GWR, Gaussian Kernel, T test

I. INTRODUCTION

Indonesia is a country with a huge population. The main source of population data is the citizen census conducted every ten years. The population census has been carried out six times since the independence of Indonesia, in 1961, 1971, 1980, 1990, 2000, and 2010. In the population census, enumeration was conducted on all residents domiciled in Indonesian territory including foreign nationals except members of the diplomatic corps from other countries and their families.

In 2010 and 2015, the number of Indonesians is around 237641 thousand and 255462 thousand people (BPS, 2016). Indonesia consists of 34 provinces, but at the time of the 2015, census was only conducted in 33 provinces since North Kalimantan Province is was still part of Central Kalimantan Province.

Population density per km2 in DKI Jakarta Province, West Java Province, Banten Province, Central Java Province, DI Yogyakarta Province and East Java Province in 2015 respectively are 15328, 1320, 1237, 1030, 1174, 813 people. Indonesia has large people with not adequate income then poverty will be a problem. The number of poor people in Indonesia in 2015 is 28553,2 (thousand) people. The number of poor people in 2015 in DKI Jakarta Province, West Java Province, Banten Province, Central Java Province, DI Yogyakarta Province and East Java Provinces are 383.8 (thousand), 4460.7 (thousand), 696.5 (thousand), 4541.4 (thousand), 517.9 (thousand) and 4782.5 (thousand) persons. With so many very poor people, it is important to know the factors those influence it.

Factors causing poverty in Pakistan by Tahir et al 2014 are the low Gross Domestic Product (GDP) as well as the low income distribution in the country.

Poor will become poorer over time, even after Pakistan's GDP growth. Increasing unemployment, lack of job opportunities encourages increased poverty in this country.

Akhtar et.al 2017 stated that education helps reduce poverty and improved the socioeconomic status of individuals in society. By educating more individuals in this country, the poor could be decreased. In addition, domestic credit to the private sector had a significant negative impact on poverty. Pakistan's private sector played an important role in providing jobs to the population of Pakistan. Increasing of employment and endeavor ultimately reduced poverty. The research findings also showed that foreign direct investment (FDI) significantly affected poverty in Pakistan. With FDI creating jobs, acquiring new technology, developing human resources, increasing domestic investment, increasing tax revenues and integrating international trade in Pakistan, these will would reduce poverty.

Quy 2016. Showed that from data of 245 years and 63 provinces that 1. Private investment has a positive impact on economic growth, 2. Poverty and import-export have an impact on unemployment, 3. Private investment has a very significant impact on job availability and the four unemployed, export-import, and private investment have an impact on poverty.

Hoynes et al. 2006 showed that although real GDP growth per capita had grown sharply in the past three decades, the poverty rate in America had changed very little. This shows the weakening of the relationship between poverty and macroeconomics. We found that this relationship had weakened over time, but apart from this, changes in job market opportunities - as measured by average wages, unemployment and distribution rates alleviated poverty significantly. It was also found that the lack of improvement in poverty rates despite increased living conditions was due to stagnant median wage growth and rising inequality. Increasing supply of women workers should reduce poverty more, but wage increases in female labor were not too high. In conclusion, the labor market plays an important role in determining the overall poverty level, but their role has changed over time, and that variables tends to interact with demographic changes and other social changes.

By understanding the above explanation, it is necessary to discuss the factors that affect poverty in Indonesia. Factors affecting poverty in Indonesia may not be global for all provinces as Indonesia is a large country with a large area, high population and different climatic and social conditions, the factors affecting poverty in Indonesia exist locally. Therefore, the study of geographically weighted regression model between poverty and influencing factors needs to be conducted.

The regression model is a function between the independent variables (some variables) with the dependent variable that can estimate the value of the dependent variable based on the value of the independent variable. This regression model applies globally and does not take into account spatial effects. When it includes spatial effects, it provides a more accurate coefficient estimate. Taking into account spatial effects, each study location will have unique coefficient estimates, also known as local estimates. Thus, geographically weighted regression (GWR) is introduced as one of the new methods that can test spatial risk factors for various problems. This statistical method adapts the global framework to the local regression model, which allows to estimate regression parameters for each spatial point (Syerrina et al 2017, Lu et al 2014, Yrigoyen et al 2008)

Geographically Weighted Regression (GWR) is a method for modeling the response of the predictor variables, by including elements of the area (spatial) into the point-based model. From former research, it concluded that the OLS regression models had poor performance because the residual variance was not homogeneous. There were no significant differences between GWR models with OLS model or in other words generally predictor variables did not affect the response variable. However, GWR model could captured modelling in each region (Utami et al 2016). Indeed, in any analysis of spatial data GWR maybe used as a diagnostic for a global modeling approach to examine for the presence of spatial nonstationarity in relationships (Brunsdon et al 1999, Mei et al 2004)

II. PURPOSE

The purpose of this study is to study the factors that affect number of poor people in Indonesia both global and local.

III. DATA AND RESEARCH METHODS

3.1. Data

The research data used is secondary data taken from Statistical Yearbook of Indonesia 2016 (BPS 2016) which is data of 2015. The dependent variable (response) is Number of Poor People (thousand) per province, and 13 independent variables. The independent variables are provincial minimum wage (X1), percentage of unemployment rate at province (X2), percentage of labor force participation rate at province (X3), percentage of household uses electricity at province (X4), percentage of household uses water from Local water company (PDAM) at province (X5), percentage of household do not have toilets at province (X6), percentage of household uses wooden cooking at provinse (X7), number of population (thousand) of provinces (X8), number of job seekers at province (X9), population density per km2 at province (X10), percentage of households can access drinking water at province (X11), percentage of household uses ground floor at province (X12), percentage of household with own house at province (X13).

The smallest unit of data is the province, that there are 34 provinces namely: Aceh Province, North Sumatra Province, West Sumatra Province, Riau Province, Jambi Province, South Sumatera Province, Bengkulu Province, Lampung Province, Bangka Belitung Islands Province, Riau Islands Province, DKI Jakarta, West Java Province, Central Java Province, Yogyakarta Province, East Java Province, Banten Province, Bali Province, West Nusa Tenggara Province, East Nusa Tenggara Province, West Kalimantan Province, Central Kalimantan Province, South Kalimantan Province, East Kalimantan Province, North Sulawesi, Central Sulawesi Province, South Sulawesi Province, Southeast Sulawesi Province, Gorontalo Province, West Sulawesi Province, Maluku Province, North Maluku Province, West Papua Province, Papua Province.

3.2. Methods

The software used in this research is R with HP-Provilion g series intel inside core tm i5. In the early stages we calculated the weighted matrix W, which used Gaussian Kernel function. The distance used was the distance between euclidus provinces with the distance of longitude and latitude coordinate position (Chasco et al. 2007). After obtaining weighting with the Gaussian Kernel Function, we estimated the parameters of regression grografi (GWR) parameters and the regression coefficient parameters for each province. The test statistic used was F-test, t-test, Coefficient Variations.

IV. LITERATURE REVIEWS

4.1. Geographycal Weighted Regression

GWR is a non-stationary technique that models spatially varying relationships. Compared with a basic (global) regression, the coefficients in GWR are functions of spatial location. Fotheringham et al. (2002) and Huang (2010) give a general form of a basic GWR model as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \qquad , i = 1,2,\ldots,n$$

Where y_i is the dependent variable at location i; x_{ik} is the kth independent variable at location i; p is the number of independent variables; $\beta_0(u_i, v_i)$ is the intercept parameter at location i (longitude, latitude); $\beta_k(u_i, v_i)$ is the local regression coefficient for the kth independent variable at location i (longitude, latitude); and εi is the random error at location i. GWR allows coefficients to vary continuously over the study area, and a set of coefficients can be estimated at any location – typically on a grid so that a coefficient surface can be visualised and interrogated for relationship heterogeneity. GWR makes a point-wise calibration concerning a 'bump of influence': around each regression point where nearer observations have more influence in estimating the local set of coefficients than observations farther away. In essence, GWR measures the inherent relationships around each regression point i, where each set of regression coefficients is estimated by weighted least squares. The matrix expression for this estimation is,

$$\widehat{\boldsymbol{\beta}}_i = \left(\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{X}\right)^{-1}\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{y}$$

where **X** is the matrix of the independent variables with a column of 1s for the intercept; **y** is the dependent variable vector; $\widehat{\boldsymbol{\beta}}_i = (\beta_{i0} \ldots \beta_{ip})^T$ is the vector of m + 1 local regression coefficients; and Wi is the diagonal matrix denoting the geographical weighting of each observed data for regression point i.

4.2. Parameter Estimation $\boldsymbol{\beta}(\boldsymbol{u_i}, \boldsymbol{v_i})$

The parameter estimation method in GWR model is conducted by Weighted Least Square (WLS) method by giving different weight for each location of the data.

Suppose the weights for each i-location are $w_j(u_i, v_i)$ $j = 1,2, \ldots, n$ then the location parameter (u_i, v_i) is estimated by adding a weighting element and then minimizing the sum of the following error squares:

$$\sum_{j=1}^{n} w_j(u_i, v_i)\varepsilon_j^2 = \sum_{j=1}^{n} w_j(u_i, v_i)\left(y_j - \beta_0(u_i, v_i) - \beta_1(u_i, v_i)x_{j1} - \beta_2(u_i, v_i)x_{j2} - \cdots - \beta_p(u_i, v_i)x_{jp}\right)^2$$

Suppose

$$\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{p1} & x_{p2} & \cdots & x_{np} \end{bmatrix}, \mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \boldsymbol{\beta}(u_i, v_i) = \begin{bmatrix} \beta_0(u_i, v_i) \\ \beta_1(u_i, v_i) \\ \vdots \\ \beta_p(u_i, v_i) \end{bmatrix}$$

Has an order $\mathbf{X}_{(n\times(p+1))}$, $\mathbf{Y}_{(n\times 1)}$, $\boldsymbol{\beta}_{((p+1)\times 1)}$

And has the GWR equation in matrix form:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta}$$

$$\mathbf{W}(u_i, v_i) = \text{diag}[w_1(u_i, v_i), w_2(u_i, v_i), \ldots, w_n(u_i, v_i)]$$

And

$$\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)^T$$

The solution of the above equations in matrix form is:

$$\begin{aligned}\boldsymbol{\varepsilon}^T\mathbf{W}(u_i, v_i)\boldsymbol{\varepsilon} &= [\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}(u_i, v_i)]^{\boldsymbol{T}}\mathbf{W}(u_i, v_i)[\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}(u_i, v_i)] \\ &= \mathbf{Y}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} - \mathbf{Y}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i) - \boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} \\ &\quad + \boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i)\end{aligned}$$

Since $\mathbf{X}\boldsymbol{\beta}(u_i, v_i) = \boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)\mathbf{X}^{\mathrm{T}}$ then the above equation becomes:

$$\boldsymbol{\varepsilon}^T\mathbf{W}(u_i, v_i)\boldsymbol{\varepsilon} = \mathbf{Y}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} - 2\boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} + \boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i)$$

If the above equation is differentiated to the matrix $\boldsymbol{\beta}^{\mathrm{T}}(u_i, v_i)$ and the result is equal to zero then it is obtained:

$$-2\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} + 2\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i) = 0$$

$$\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i) = \mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}$$
$$\left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i) = \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}$$
$$\widehat{\boldsymbol{\beta}}(u_i, v_i) = \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}$$

So the form of parameter estimation from GWR model for each location is:

$$\widehat{\boldsymbol{\beta}}(u_i, v_i) = \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}$$

in Caraka and Yasin (2017) and Fotheringham et al. (2002)

Since there are n sample locations then this estimate is an estimate of each row of the local matrix of the parameters of the entire study site. The matrix is:

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \beta_2(u_1, v_1) & \cdots & \beta_p(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \beta_2(u_2, v_2) & \cdots & \beta_p(u_2, v_2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \beta_2(u_n, v_n) & \cdots & \beta_p(u_n, v_n) \end{bmatrix}$$

4.3. The properties of the Parameter Estimator $\boldsymbol{\beta}(u_i, v_i)$

The properties of $\widehat{\boldsymbol{\beta}}(u_i, v_i)$ from the above GWR model is an unbiased estimator for $\boldsymbol{\beta}(u_i, v_i)$ (Caraka and Yasin 2017) and (Fotheringham et al 2002)

$$\begin{aligned} \mathrm{E}\left[\widehat{\boldsymbol{\beta}}(u_i, v_i)\right] &= \mathrm{E}\left[\left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}\right] \\ &= \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathrm{E}[\mathbf{Y}] \\ &= \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\boldsymbol{\beta}(u_i, v_i) \\ &= \mathbf{I}\boldsymbol{\beta}(u_i, v_i) \\ &= \boldsymbol{\beta}(u_i, v_i) \end{aligned}$$

While the matrix of the uniform variety of these estimators is as follows:

$$\mathrm{cov}\left[\widehat{\boldsymbol{\beta}}(u_i, v_i)\right] = \mathrm{cov}\left[\left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}\right]$$
$$= \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathrm{cov}[\mathbf{Y}]\left(\left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\right)^T$$
$$= \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)(\sigma^2\mathbf{I})\left(\left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\right)^T$$
$$= \boldsymbol{L}\boldsymbol{L}^T\sigma^2$$

where $\boldsymbol{L} = \left(\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(u_i, v_i)$

4.4. Weighting of GWR Model

Weighting on the GWR model has a very important role because the weighted value represents the location of the observed data with each other. Weighting on GWR can use several different methods. The kernel function is used to estimate the parameters in the GWR model if the distance function is a continuous and monotonous function down (Chasco et al. 2007). The weights that are formed by using the Gaussion Kernel function are Gaussian distance functions

$$w_j(u_i, v_i) = \varphi\left(\frac{d_{ij}}{\sigma h}\right)$$

Where φ is the standard normal density and σ denotes the standard deviation of the distance vector d_{ij}. With $d_{ij} = \sqrt{\left(u_i - u_j\right)^2 - \left(v_i - v_j\right)^2}$ and h is the radius of the center of the location or the bandwidth.

The selection of the optimum bandwidth becomes very important because it will affect the accuracy of the model of the data, which regulates the variety and bias of the model. One method used to determine the optimum bandwidth is the cross-validation method and can be written mathematically as follows (Fotheringham et al., 2002):

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

where $\hat{y}_{\neq i}(h)$ is the alleged value of y_i at on-site observations (u_i, v_i) omitted from the estimation process. CV is coefficient Variation. To get the optimal value h is obtained from h that produces minimum CV value.

This test is performed with the following hypothesis:

H_0 : $\beta_k(u_i, v_i) = \beta_k$, $k = 1,2, \dots, p$ (There is no significant difference between global regression model and GWR)

H_1 : There is at least one $\beta_k(u_i, v_i)$ associated with the location (u_i, v_i) is not zero (there is a significant difference between the global regression model and GWR).

Test statistics used are:

$$F^* = \frac{SSE(H_0)/df_1}{SSE(H_1)/df_2}$$

where

$$SSE(H_0) = \mathbf{Y}^T(\mathbf{I} - \mathbf{H})\mathbf{Y} \text{ with } \mathbf{H} = \mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^T$$

$$df_1 = n - p - 1$$

$$SSE(H_1) = \mathbf{Y}^T(\mathbf{I} - \mathbf{S})^T(\mathbf{I} - \mathbf{S})\mathbf{Y}$$

$$df_2 = \left(n - 2tr(\mathbf{S}) + tr\left(\mathbf{S}^{\mathrm{T}}\mathbf{S}\right)\right)$$

S is the projection matrix of the GWR model, which is a matrix that projects y to $\hat{y}$ at location (u_i, v_i).

$$\mathbf{S} = \begin{bmatrix} x_1^T[\mathbf{X}^T\mathbf{W}(u_1, v_1)\mathbf{X}]^{-1}\mathbf{X}^T\mathbf{W}(u_1, v_1) \\ x_2^T[\mathbf{X}^T\mathbf{W}(u_2, v_2)\mathbf{X}]^{-1}\mathbf{X}^T\mathbf{W}(u_2, v_2) \\ \vdots \\ x_n^T[\mathbf{X}^T\mathbf{W}(u_n, v_n)\mathbf{X}]^{-1}\mathbf{X}^T\mathbf{W}(u_n, v_n) \end{bmatrix}$$

Is the matrix $n \times n$ and **I** is the identity matrix of the order n.

If F^* is greater than F_{tabel} then the decision is to reject H_0, in other words GWR model has better model than global regression model.

The next test is to test the parameters partially. This test is performed 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 : $\beta_k(u_i, v_i) \neq 0; k = 1,2, \dots, p$

The parameter estimate $\boldsymbol{\beta}(u_i, v_i)$ will follow the normal distribution with the mean $\boldsymbol{\beta}(u_i, v_i)$ and the uniform matrix of $\boldsymbol{LL}^T\sigma^2$, so

$$\frac{\widehat{\boldsymbol{\beta}}_k(u_i, v_i) - \boldsymbol{\beta}_k(u_i, v_i)}{\sigma\sqrt{g_{kk}}} \sim N(0,1)$$

with g_{kk} is the k-diagonal element of the $\boldsymbol{LL}^T$ matrix. So the test statistic used is:

$$T = \frac{\widehat{\boldsymbol{\beta}}_k(u_i, v_i)}{\hat{\sigma}\sqrt{g_{kk}}}$$

T will follow the t distribution with df_2 free degrees. If the significance level is given by α, then the decision is made by rejecting H_0 or in other words the parameter $\boldsymbol{\beta}_k(u_i, v_i)$ is significant to the model if $|T_{hit}| > t_{\frac{\alpha}{2};df_2}$.

V. RESULTS AND DISCUSSION

5.1. Bandwidth

Optimal bandwidth with adaptive principles, bandwidth calculations showing the number of nearest neighbors in the i-th region. The bandwidth value obtained from the iteration result is q: 0.3796418 with the CV criterion value: 908.41298. The bandwidth value of each region is used to form the weighting matrix for each i-th region.

5.2. Global Regression Analysis

Global regression model using the least square error method from R program as follows:

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-2.250e+03	1.950e+03	-1.154	0.26274
X1	1.464e-04	2.618e-04	0.559	0.58257
X2	-1.877e+01	3.836e+01	-0.489	0.63026
X3	1.188e+01	1.772e+01	0.670	0.51072
X4	9.975e+00	6.758e+00	1.476	0.15630
X5	-5.256e+00	8.355e+00	-0.629	0.53679
X6	4.608e+00	7.441e+00	0.619	0.54312
X7	-1.238e+00	5.939e+00	-0.208	0.83706
X8	9.958e-02	9.900e-03	10.058	4.8e-09 ***
X9	1.174e-03	1.498e-03	0.783	0.44301
X10	-4.622e-02	2.607e-02	-1.773	0.09228 .
X11	1.305e+00	5.829e+00	0.224	0.82517
X12	4.101e+01	1.234e+01	3.323	0.00358 **
X13	3.418e+00	1.027e+01	0.333	0.74298

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 235.4 on 19 degrees of freedom

Multiple R-squared: 0.979, Adjusted R-squared: 0.9646

F-statistic: 68.15 on 13 and 19 DF, p-value: 4.144e-13

The model obtained is as follows:

$$y = -2250.22 + 0.0001\, X_1 - 18.7691\, X_2 + 11.8791\, X_3 + 9.9749\, X_4 - 5.2557 X_5 + 4.6077 X_6 - 1.2383\, X_7 + 0.0996 X_8 + 0.0012\, X_9 - 0.0462 X_{10} + 1.3055 X_{11} + 41.0077 X_{12} + 3.4182\, X_{13}$$

The above global regression model had F-statistics 68.15 with p-value 4 x 10^{-13} which gave the meaning independent variables of global regression model can explain the number of poverty in Indonesia, with 98% accuracy. It can also be interpreted that the independent variables of global regression model such as provincial minimum wage (X1), percentage of unemployment rate at province (X2), percentage of labor force participation rate at province (X3), percentage of household uses electricity at province (X4), percentage of household uses water from Local water company (PDAM) at province (X5), percentage of household do not have toilets at province (X6), percentage of household uses wooden cooking at provinse (X7), number of population (thousand) of provinces (X8), number of job seekers at province (X9), population density per km^2 at province (X10), percentage of households can access drinking water at province (X11), percentage of household uses ground floor at province (X12), percentage of household with own house at province (X13) able to estimate the number of poverty in Indonesia.

Two of 13 independent variables above, number of population (thousand) of provinces (X8), percentage of household uses ground floor at province (X12) had significant regression coefficient. Increasing the number of population will increase number of poor people and an increase in the percentage of household uses ground floor will increase number of poor people in Indonesia.

The high number of population leads to business competition, raising the price of basic commodities which will increase the number of poor people. Similarly, the increasing percentage of household with the ground floor increases the cost of medicine (unhealthy conditions) and decreases the productivity which consequently will increase the number of poor people.

5.3. *Geographically Weighted Regression* (GWR) Analysis

In the early stages, it is tested spatial variability in the data on the number of poverty in Indonesia. The null hypothesis is no spatial diversity and the one hypothesis is that there is spatial diversity. When one hypothesis is accepted then the regression model that is developed properly is GWR. From the test using software R, it is obtained from Breusch Pagan test that p-value is 0.0032 which means accepting Hypothesis one.

Studentized Breusch-Pagan test

data: Y ~ X1 + X2 + X3 + X4 + X5 + X6 + X7 + X8 + X9 + X10 + X11 + X12 + X13

BP = 12.1266, df = 2, p-value = 0.00232

Furthermore, it is conducted a comparative test between global regression with GWR. In Table 1 we can see that p-value <0.05 that means there is a significant improvement between GWR Regression model with Global Regression model

Table 1. Model goodness test results

Model	Sources	Degree Of freedom	Sum square	Mean Sum Square	F-test	p-Value
Global Regression	Error	3	1841457		4.8888	$5.638x10^{-5**}$
GWR	*Improvement*	7.2376	1120576	154827		
GWR	Error	22.7624	720881	31670		

(**) significant for 5%

The statistics of comparison size between Global Regression with GWR are Number of Error Sq. (JKG), AIC (Akaike Informatioan Criteria) and R^2 (coefficient of determination). The results of comparison of GWR model and linear regression model are seen in Table 2.

Table 2. Comparison of GWR model and global regression

	GWR Regression Model	OLS Regression Model
JKG	720881	1841457
R^2	0.9986171	0.9646
AIC	374.0251	465.8733

In Table 2 it can be seen that the JKG and AIC values of the GWR regression model are smaller than the global regression model, which mean that GWR is better than the global regression. Similarly, R^2 of GWR model is bigger than the value of R^2 of MKT model. Based on these three things can be concluded GWR Regression model is better than global regression model.

Geographically Weighted Regression (GWR) is the development of the Global Regression Model. Therefore, the resulting model can predict the regression coefficients for each province in Indonesia. In the GWR model, the y response variable is estimated by the explanatory variable whose regression coefficients depend on the location of the data. Model of GWR (Geographically Weighted Regression) is;

$$y_i = \beta_0(u_i, v_i) + \beta_1 x_1(u_i, v_i) + \beta_2 x_2(u_i, v_i) + \cdots + \beta_{13} x_{13}(u_i, v_i) + \varepsilon_i$$

Table 3. Summary of parameter estimators on the GWR model

	Minimum	Q_1	Median	Q_3	Maximum	Global
Intercept	-5190	-2034	-663.1	-239.2	3025	-2250.22
X_1	-0.00034	-0.00025	-2.4E-06	0.000486	0.000978	0.0001
X_2	-168	-121.9	-79.55	7.32	27.23	-18.7691
X_3	-30.21	9.332	14.75	28.89	73.65	11.8791
X_4	-2.708	4.354	5.592	6.929	13.08	9.9749
X_5	-30.62	-14.93	-8.506	-3.911	6.251	-5.2557
X_6	1.519	6.011	8.466	19.7	28.46	4.6077
X_7	-20.56	-10.28	-6.138	-2.43	1.609	-1.2383
X_8	0.08692	0.09058	0.09822	0.1167	0.1313	0.0996
X_9	-0.00296	-0.00055	0.001128	0.002479	0.003197	0.0012
X_{10}	-0.1267	-0.08728	-0.05295	-0.03454	0.02237	-0.0462
X_{11}	-6.227	-1.353	0.6624	2.298	3.432	1.3055
X_{12}	24.66	33.6	62.89	94.95	113.1	41.0077
X_{13}	-30.58	-16.57	-8.438	-0.9392	18.77	3.4182

Based on Table 3, the GWR using the Gaussian Kernel model of the number of poor people in 33 provinces with 13 independent variables obtained minimum, the first quartile, the median, the third quartile, and the maximum values of the parameters of the GWR model. GWR model had AIC of 374.0251 and R^2 of 0.9986171 which can be interpreted that the number of poor people is affected by all the independent variables that enter into the model accurately, while the rest is influenced by other variables outside of this study.

In Table 4 we can study the change of regression coefficient value for each province. At provincial minimum wage (X1), provinces with negative regression coefficients are Maluku, West Sulawesi, South Sulawesi, North Maluku, Central Sulawesi, Southeast Sulawesi, Bali, North Sulawesi, West Nusa Tenggara, West Papua, Gorontalo, East Nusa Tenggara, East Java, Papua, East Kalimantan, Yogyakarta, South Kalimantan, Central Java and provinces with positive regression coefficient are Central Kalimantan, West Java, DKI Jakarta, Banten, West Kalimantan, Bangka Belitung Islands, Aceh, Lampung, North Sumatra, Riau Islands, South Sumatra, Bengkulu, Riau, West Sumatera, Jambi.

Provinces with the percentage of provincial unemployment rate (X2) with negative regression coefficient are West Java, Yogyakarta, DKI Jakarta, Central Java, Banten, Lampung, South Sumatera, Bengkulu, Jambi, Bangka Belitung Islands, West Sumatera, Riau, West Kalimantan, Riau, East Java, Aceh, North Sumatra, Central Kalimantan, South Kalimantan, Bali, West Nusa Tenggara, East Kalimantan and provinces with positive regression coefficient are North Maluku, Maluku, North Sulawesi, Papua, Gorontalo, West Papua, Central Sulawesi, Southeast Sulawesi, East Nusa Tenggara, West Sulawesi, South Sulawesi.

At the percentage of labor force participation rate at (X3), provinces with negative regression coefficient are Yogyakarta, Central Java, East Java, West Java, and provinces with positive regression coefficient are Central Kalimantan, South Kalimantan, West Kalimantan, Bali, Nusa Tenggara West, East Kalimantan, Maluku, Central Sulawesi, North Maluku, West Sulawesi, West Papua, Gorontalo, Southeast Sulawesi, North Sulawesi, Papua, South Sulawesi, Aceh, East Nusa Tenggara, DKI Jakarta.

In percentage of household uses electricity at province (X4), provinces with negative regression coefficients are West Java, Yogyakarta, Central Java, and provinces with positive regression coefficients are East Java, DKI Jakarta, West Kalimantan, North Maluku, Maluku, Gorontalo, Banten North Sulawesi, Central Kalimantan, West Sulawesi, Southeast Sulawesi, West Nusa Tenggara, North Sumatra, South Sulawesi, Aceh, East Kalimantan, Papua, East Nusa Tenggara, Riau Islands, Bangka Belitung Islands, Riau, West Sumatera, Bengkulu, South Sumatera, Jambi, Lampung.

In percentage of household uses water from Local water company (PDAM) at province (X5), provinces with negative regression coefficients are Jambi, Lampung, West Sumatera, Bengkulu, South Sumatra, Riau, Bangka Belitung Islands, Maluku, Riau Islands, North Maluku, North Sulawesi, West Papua , North Sumatra, Gorontalo, Banten, Southeast Sulawesi, Papua, DKI Jakarta, Aceh, Central Sulawesi, East Nusa Tenggara, West Sulawesi, South Sulawesi, East Kalimantan, West Kalimantan, Central Kalimantan, South Kalimantan, and provinces with positive regression coefficients is West Java, West Nusa Tenggara, Bali, East Java, Central Java, Yogyakarta

The change in the direction of the GWR coefficients model on the other independent variables for each province can be seen in Table 4. The negative regression coefficient in a particular province means the increasing value of the independent variable will decrease the number of poor people in the province. While the regression coefficient is positive in a particular province has the meaning the increasing value of independent variable will increase the number of poverty in the province concerned. There is a difference in the direction of regression coefficient values on certain independent variables between provinces reflecting there is differencing socio-cultural in poverty.

Table 4. GWR regression coefficients of each province in Indonesia

Province	Intercept	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Aceh	-1438,560	0,0005	-81,103	17,848	6,629	-7,687	17,859	-10,280	0,111	-0,001	-0,081	0,662	91,603	-10,273
North Sumatera	-2034,024	0,0005	-79,552	28,886	6,191	-10,922	18,448	-9,874	0,112	-0,001	-0,087	1,152	97,765	-13,327
West Sumatera	-3390,389	0,0008	-111,421	49,555	11,208	-24,997	21,546	-7,433	0,118	0,000	-0,112	1,102	95,768	-22,383
Riau	-3530,082	0,0008	-102,504	49,954	10,526	-23,729	20,466	-6,760	0,116	0,000	-0,110	1,391	94,318	-20,954
Jambi	-5190,403	0,0010	-121,925	73,650	12,651	-30,621	14,655	-0,723	0,123	0,001	-0,127	2,764	78,270	-24,921
South Sumatera	-3564,028	0,0006	-126,375	62,436	12,646	-24,611	23,213	-12,205	0,128	-0,002	-0,117	3,432	101,846	-27,498
Bengkulu	-3535,034	0,0007	-123,829	58,911	11,440	-24,689	20,803	-9,093	0,125	-0,001	-0,114	2,640	94,950	-25,205
Lampung	-3039,810	0,0005	-139,211	60,742	13,084	-25,855	28,457	-16,737	0,131	-0,003	-0,119	2,881	113,053	-30,577
Bangka Belitung Islands	-2763,289	0,0005	-118,060	49,396	9,540	-16,920	20,353	-13,214	0,124	-0,002	-0,103	2,774	99,458	-21,424
Riau Island	-2711,011	0,0006	-94,815	41,460	7,573	-14,930	17,472	-9,332	0,117	-0,001	-0,096	2,298	92,981	-16,567
DKI Jakarta	6,611	0,0003	-149,314	20,139	2,825	-8,030	20,992	-19,503	0,120	-0,002	-0,074	-1,146	102,861	-14,755
West Java	2222,124	0,0001	-167,982	-8,092	-2,708	0,367	19,702	-20,557	0,113	-0,001	-0,046	-3,273	96,675	-6,954
Central Java	2609,676	0,0000	-146,465	-25,606	-1,826	4,924	13,861	-14,451	0,102	0,000	-0,012	-5,319	79,871	3,531
Yogyakarta	3024,512	0,0000	-156,262	-30,208	-2,169	6,251	14,746	-15,187	0,101	0,000	-0,004	-6,222	78,151	4,927
East Java	517,326	-0,0001	-91,176	-12,742	2,737	4,388	6,011	-9,307	0,094	0,001	0,012	-6,227	60,492	13,254
Banten	-376,917	0,0003	-143,690	24,927	4,396	-10,596	22,583	-17,938	0,121	-0,002	-0,083	-0,456	104,432	-18,043
Bali	-1579,968	-0,0003	-24,775	5,658	5,348	3,246	1,884	-6,138	0,087	0,002	0,022	-5,163	41,959	18,770
West Nusa Tenggara	-1778,690	-0,0002	-10,879	9,332	5,944	1,791	2,764	-5,292	0,087	0,002	0,013	-4,343	40,601	15,595
East Nusa Tenggara	-1774,432	-0,0002	18,139	18,629	6,929	-6,215	5,063	-1,452	0,087	0,003	-0,025	-1,319	33,489	1,461
West Kalimantan	-367,755	0,0004	-95,789	5,636	3,550	-3,911	14,279	-10,013	0,110	0,000	-0,066	0,859	87,026	-6,527
Central Kalimantan	-526,125	0,0001	-57,317	0,342	5,263	-2,290	7,550	-5,746	0,098	0,001	-0,035	-1,259	62,889	2,029
South Kalimantan	-663,143	0,0000	-40,717	2,207	5,267	-1,543	5,911	-5,125	0,094	0,002	-0,024	-2,358	57,852	4,045
East Kalimantan	-892,462	-0,0001	-8,937	10,852	6,713	-4,300	8,466	-3,366	0,093	0,002	-0,038	-1,138	47,314	-3,358
North Sulawesi	-140,924	-0,0002	7,320	14,907	4,425	-12,339	6,410	-0,353	0,094	0,003	-0,060	2,561	27,370	-13,026
Central Sulawesi	-390,725	-0,0003	14,840	12,707	5,514	-7,107	7,457	-2,430	0,093	0,002	-0,044	-0,171	33,599	-7,261
South Sulawesi	-1059,085	-0,0003	27,228	16,138	6,462	-4,744	6,763	-3,576	0,087	0,003	-0,024	-2,670	35,962	-0,939
Southeast Sulawesi	-582,556	-0,0003	16,305	14,748	5,807	-9,159	6,947	-2,554	0,091	0,003	-0,042	-0,291	32,801	-6,379
Gorontalo	-239,245	-0,0002	8,140	14,525	4,354	-10,786	7,938	-1,115	0,097	0,002	-0,063	2,533	29,082	-12,082
West Sulawesi	-467,339	-0,0003	22,248	13,222	5,592	-6,179	6,769	-2,753	0,090	0,002	-0,036	-1,353	34,181	-5,383
Maluku	295,232	-0,0003	5,830	12,009	4,201	-15,436	2,572	-0,352	0,088	0,003	-0,053	1,789	26,234	-11,801
North Maluku	223,569	-0,0003	5,226	12,750	4,125	-14,515	3,731	0,004	0,091	0,003	-0,057	2,534	25,405	-13,165
West Papua	-479,942	-0,0002	8,598	13,896	5,343	-12,261	1,979	1,485	0,087	0,003	-0,046	1,792	24,664	-8,438
Papua	-1536,113	-0,0001	7,356	15,501	6,790	-8,506	1,519	1,609	0,090	0,003	-0,038	1,273	27,228	-1,249

Table 5. Significant level (alpha 5%) GWR regression coefficients of each province in Indonesia

Province	t intercept	t X1	t X2	t X3	t X4	t X5	t X6	t X7	t X8	t X9	t X10	t X11	t X12	t X13
Aceh	-0,9765	**2,7960**	**-2,4441**	1,1911	1,3796	-1,4722	**3,0865**	**-2,1407**	**18,9334**	-0,5759	**-5,0982**	0,1843	**8,2189**	-1,5669
North Sumatera	-1,0334	**2,6293**	-1,9481	1,4688	0,9730	-1,6473	**2,4454**	-1,5117	**16,9563**	-0,4411	**-4,9533**	0,2734	**6,8587**	-1,8165
West Sumatera	-1,1688	**2,6763**	**-2,0206**	1,7905	1,4373	**-2,1623**	1,6781	-0,6933	**15,5113**	0,0798	**-5,1564**	0,2292	**4,8131**	**-2,3104**
Riau	-1,2144	**2,5142**	-1,8971	1,8081	1,3659	**-2,0928**	1,6626	-0,6397	**14,5137**	0,1987	**-5,0312**	0,2800	**4,8211**	**-2,2339**
Jambi	-1,5130	**2,7582**	-1,8411	**2,2035**	1,5116	**-2,0106**	0,7621	-0,0526	**13,7325**	0,4385	**-4,6710**	0,5359	**2,8452**	**-2,0644**
South Sumatera	-1,3923	**2,5448**	**-2,4747**	**2,2560**	1,5889	**-2,2010**	**2,2980**	-1,6925	**16,1879**	-1,8975	**-4,8266**	0,7430	**6,6973**	**-2,8187**
Bengkulu	-1,3275	**2,6845**	**-2,3196**	**2,1628**	1,4634	**-2,1138**	1,8264	-1,0700	**17,5458**	-0,9957	**-5,0157**	0,5767	**6,0342**	**-2,6290**
Lampung	-1,2233	**2,3364**	**-2,6656**	**2,1714**	1,6296	**-2,3003**	**2,7147**	**-2,3120**	**15,0521**	**-2,3495**	**-4,6730**	0,6336	**7,1920**	**-2,9415**
Bangka Belitung Islands	-1,1835	**2,2216**	**-2,5229**	**2,0272**	1,3076	**-2,0681**	**2,5629**	**-2,1367**	**17,1395**	-1,9036	**-4,7008**	0,6242	**6,8571**	**-2,5689**
Riau Island	-1,1645	**2,3378**	**-2,0819**	1,8252	1,0674	-1,8662	**2,1963**	-1,3835	**18,1290**	-0,7084	**-4,8982**	0,4937	**6,6553**	**-2,1519**
DKI Jakarta	0,0032	1,4139	**-3,2393**	0,9369	0,4263	-1,1722	**2,6588**	**-2,9459**	**16,5503**	-1,6657	**-3,4435**	-0,2900	**7,0234**	-1,7317
West Java	1,1917	0,7123	**-3,6908**	-0,4422	-0,4300	0,0584	**2,5589**	**-3,0909**	**16,8311**	-1,1151	**-2,2063**	-0,8764	**6,6416**	-0,8076
Central Java	1,6015	0,0953	**-3,7616**	-1,7490	-0,3415	0,8344	1,9431	**-2,6877**	**15,7011**	0,1607	-0,5833	-1,5746	**6,1526**	0,4131
Yogyakarta	1,7894	-0,1671	**-3,9299**	**-2,0175**	-0,3985	1,0298	**2,0250**	**-2,7340**	**15,3638**	0,1804	-0,1872	-1,8269	**5,9993**	0,5653
East Java	0,3386	-0,5790	**-2,7111**	-0,9019	0,5440	0,7345	0,8420	-1,9815	**13,6110**	1,2404	0,4797	-1,7469	**5,1761**	1,4722
Banten	-0,1831	1,6796	**-3,1210**	1,1511	0,6682	-1,4953	**2,8314**	**-2,8055**	**16,8603**	-1,7883	**-3,9622**	-0,1138	**7,2955**	**-2,1823**
Bali	-1,1432	-1,3001	-0,8230	0,4185	1,0408	0,5596	0,2586	-1,3656	**12,3457**	**2,1806**	0,9068	-1,3090	**4,0447**	**2,0225**
West Nusa Tenggara	-1,3606	-1,2700	-0,3905	0,7164	1,1902	0,3204	0,3959	-1,2373	**12,6263**	**2,3760**	0,5391	-1,0854	**4,0678**	1,7154
East Nusa Tenggara	-1,4523	-1,1714	0,7793	1,7844	1,4725	-1,3155	1,0270	-0,4046	**13,5637**	**3,1592**	-1,4043	-0,3167	**4,2041**	0,1838
West Kalimantan	-0,2647	2,0257	**-2,8820**	0,4210	0,7579	-0,7885	**2,4372**	**-2,3076**	**19,8463**	-0,5074	**-3,9984**	0,2638	**7,6853**	-0,9853
Central Kalimantan	-0,4395	0,6129	**-2,1558**	0,0280	1,1953	-0,4363	1,2953	-1,4970	**16,3658**	1,2373	-1,8067	-0,3614	**6,3560**	0,2727
South Kalimantan	-0,5268	-0,0132	-1,4340	0,1719	1,1547	-0,2780	0,9373	-1,2770	**14,6752**	1,6920	-1,1054	-0,6219	**5,7593**	0,4851
East Kalimantan	-0,7056	-0,5122	-0,3581	0,8515	1,4500	-0,8004	1,3567	-0,8210	**14,2660**	**2,1549**	-1,8541	-0,2692	**4,7651**	-0,3815
North Sulawesi	-0,0877	-1,3350	0,2663	1,1171	0,7934	**-2,1935**	1,1105	-0,0718	**7,2670**	1,5377	**-2,6307**	0,4414	**2,6784**	-1,2846
Central Sulawesi	-0,2362	-1,4484	0,5561	0,8372	0,9615	-1,2408	1,0171	-0,4872	**8,1718**	1,5658	-1,8650	-0,0321	**2,6725**	-0,6949
South Sulawesi	-0,7461	-1,7693	0,9931	1,1531	1,1486	-0,8308	0,9535	-0,7344	**10,6758**	**2,5136**	-0,9869	-0,5319	**3,1350**	-0,0870
Southeast Sulawesi	-0,3790	-1,5788	0,6285	1,0868	1,0386	-1,6910	1,0649	-0,5295	**8,7712**	1,8426	-1,9319	-0,0536	**2,9097**	-0,6176
Gorontalo	-0,1329	-1,1205	0,2925	0,9169	0,7252	-1,9040	1,1037	-0,2199	**6,0833**	1,1207	**-2,5301**	0,4254	**2,3709**	-1,1706
West Sulawesi	-0,2961	-1,7380	0,7972	0,8757	0,9810	-1,0604	0,9288	-0,5421	**8,8978**	1,9201	-1,4883	-0,2594	**2,7808**	-0,4944
Maluku	0,1875	-1,7849	0,2113	1,0149	0,7656	**-2,4937**	0,4745	-0,0709	**7,9197**	1,9254	**-2,4494**	0,3091	**2,7155**	-1,1321
North Maluku	0,1416	-1,6031	0,1884	1,0396	0,7592	**-2,3917**	0,6847	0,0007	**7,6865**	1,7548	**-2,5718**	0,4388	**2,6416**	-1,2784
West Papua	-0,3535	-1,3926	0,3419	1,3122	1,1137	**-2,2690**	0,3813	0,3857	**12,0912**	**2,8879**	**-2,4849**	0,4059	**2,9807**	-0,9863
Papua	-1,3850	-0,7133	0,3341	1,6163	1,6827	-1,8250	0,3345	0,4859	**15,9915**	**3,1570**	**-2,4898**	0,3737	**3,7745**	-0,1934

Bold=significant 5 %

Furthermore, the independent variables significantly affecting the number of poor people in the provinces are presented in Table 5. As with the global regression model, in GWR model the number of population (thousand) of provinces (X8), percentage of household uses ground floor at province (X12) had significant regression coefficients at all provinces. Increasing the number of population will increase number of poor people and an increase in the percentage of household uses ground floor will increase number of poor people at all provinces. Also, From GWR model can be concluded thare are two independent variables had regression coefficeients not signifincantly at all provinces, they are the percentage of household uses electricity at province (X4), and percentage of households can access drinking water at province (X11). Those independent variables did not effect to number of poor people at all provinces.

The independent variables these significantly affect to the number of poor people in Aceh Province are variables X1, X2, X6, X7, X8, X10, X12 and X13. Changes in the value of these variables in Aceh Province will affect to the number of poor people in Aceh Province. In the same way for each province the independent variables affecting the number of poor people in a particular province can be read in Table 6.

Table 6

Province	X1	X2	X3	X5	X6	X7	X8	X9	X10	X12	X13
Aceh	X1	X2			X6	X7	X8		X10	X12	
Aceh	X1				X6		X8		X10	X12	
North Sumatera	X1	X2		X5	1,6781		X8		X10	X12	X13
West Sumatera	X1			X5	1,6626		X8		X10	X12	X13
Riau	X1		X3	X5	0,7621		X8		X10	X12	X13
Jambi	X1	X2	X3	X5	X6		X8		X10	X12	X13
South Sumatera	X1	X2	X3	X5	1,8264		X8		X10	X12	X13
Bengkulu	X1	2X	X3	X5	X6	X7	X8	X9	X10	X12	X13
Lampung	X1	X2	X3	X5	X6	X7	X8		X10	X12	X13
Bangka Belitung Islands	X1	X2			X6		X8		X10	X12	X13
Riau Island		X2			X6	X7	X8		X10	X12	
DKI Jakarta		X2			X6	X7	X8		X10	X12	
West Java		X2				X7	X8			X12	
Central Java		X2	X3		X6	X7	X8			X12	
Yogyakarta		X2					X8			X12	
East Java		X2			X6	X7	X8		X10	X12	X13
Banten							X8	X9		X12	X13
Bali							X8	X9		X12	
West Nusa Tenggara							X8	X9		X12	
East Nusa Tenggara	X1	X2			X6	X7	X8		X10	X12	
West Kalimantan		X2					X8			X12	
Central Kalimantan							X8			X12	
South Kalimantan							X8	X9		X12	
East Kalimantan				X5			X8		X10	X12	
North Sulawesi							X8			X12	
Central Sulawesi							X8	X9		X12	
South Sulawesi							X8			X12	

Southeast Sulawesi							X8		X10	X12	
Gorontalo							X8			X12	
West Sulawesi				X5			X8		X10	X12	
Maluku				X5			X8		X10	X12	
North Maluku				X5			X8	X9	X10	X12	
West Papua							X8	X9	X10	X12	
Papua											

Provincial minimum wage (X1), percentage of unemployment rate at province (X2), percentage of labor force participation rate at province (X3), percentage of household uses electricity at province (X4), percentage of household uses water from Local water company (PDAM) at province (X5), percentage of household do not have toilets at province (X6), percentage of household uses wooden cooking at provinse (X7), number of population (thousand) of provinces (X8), number of job seekers at province (X9), population density per km^2 at province (X10), percentage of households can access drinking water at province (X11), percentage of household uses ground floor at province (X12), percentage of household with own house at province (X13).

VI. CONCLUSION

There are several conclusions that are resulted in this research, among others:

1. The global regression model of the number of poor people can be well predicted with independent variables such as the provincial minimum wage (X1), the percentage of provincial unemployment rate (X2), the percentage of labor force participation rate (X3), the percentage of provincial electricity users (X4), the percentage of home (X5), the percentage of households with wood cooking (X7), the number of population (thousand) of province (X8), the number of provincial job seekers (X9), the population density per km2 of the province (X10), the percentage of households can access decent drinking water in the province (X11), the percentage of the provincial ground floor house (X12), the percentage of the population with self-owned home in the province (X13). These variables are able to estimate the number of poverty in Indonesia. This is proven by R^2 of 96% which is very high.
2. The GWR model is better at modeling the number of the poor people in the province than the global regression model. This was evidenced by the smaller Sum Square of Error, AIC and higher R^2 as compared to the Global Regression.
3. By GWR model, the number of population (thousand) of provinces (X8), percentage of household uses ground floor at province (X12) had significant regression coefficients at all provinces. Increasing the number of population will increase number of poor people and percentage of household uses ground floor will increase number of poor people at all provinces. Also, From GWR model can be concluded thare are two independent variables had regression coefficeients not signifincantly at all provinces, they are the percentage of household uses electricity at province (X4), and percentage of households can access drinking water at province (X11). Those independent variables did not effect to number of poor people at all provinces.
4. The independent variables these significantly affect to the number of poor people for each province is table below :

Table 7

Province	X1	X2	X3	X5	X6	X7	X8	X9	X10	X12	X13
Aceh	X1	X2			X6	X7	X8		X10	X12	
North Sumatera	X1				X6		X8		X10	X12	
West Sumatera	X1	X2		X5			X8		X10	X12	X13
Riau	X1			X5			X8		X10	X12	X13
Jambi	X1		X3	X5			X8		X10	X12	X13
South Sumatera	X1	X2	X3	X5	X6		X8		X10	X12	X13
Bengkulu	X1	X2	X3	X5			X8		X10	X12	X13
Lampung	X1	2X	X3	X5	X6	X7	X8	X9	X10	X12	X13
Bangka Belitung Islands	X1	X2	X3	X5	X6	X7	X8		X10	X12	X13
Riau Island	X1	X2			X6		X8		X10	X12	X13
DKI Jakarta		X2			X6	X7	X8		X10	X12	
West Java		X2			X6	X7	X8		X10	X12	
Central Java		X2				X7	X8			X12	
Yogyakarta		X2	X3		X6	X7	X8			X12	
East Java		X2					X8			X12	
Banten		X2			X6	X7	X8		X10	X12	X13
Bali							X8	X9		X12	X13
West Nusa Tenggara							X8	X9		X12	
East Nusa Tenggara							X8	X9		X12	
West Kalimantan	X1	X2			X6	X7	X8		X10	X12	
Central Kalimantan		X2					X8			X12	
South Kalimantan							X8			X12	
East Kalimantan							X8	X9		X12	
North Sulawesi				X5			X8		X10	X12	
Central Sulawesi							X8			X12	
South Sulawesi							X8	X9		X12	
Southeast Sulawesi							X8			X12	
Gorontalo							X8		X10	X12	
West Sulawesi							X8			X12	

Province	**X1**	**X2**	**X3**	**X5**	**X6**	**X7**	**X8**	**X9**	**X10**	**X12**	**X13**
Maluku				**X5**			**X8**		**X10**	**X12**	
North Maluku				**X5**			**X8**		**X10**	**X12**	
West Papua				**X5**			**X8**	**X9**	**X10**	**X12**	
Papua							**X8**	**X9**	**X10**	**X12**	

Provincial minimum wage (X1), percentage of unemployment rate at province (X2), percentage of labor force participation rate at province (X3), percentage of household uses electricity at province (X4), percentage of household uses water from Local water company (PDAM) at province (X5), percentage of household do not have toilets at province (X6), percentage of household uses wooden cooking a5. provinse (X7), number of population (thousand) of provinces (X8), number of job seekers at province (X9), population density per km^2 at province (X10), percentage of households can access drinking water at province (X11), percentage of household uses ground floor at province (X12), percentage of household with own house at province (X13).

There are differences in the direction of the regression coefficients on the variables affecting poverty among provinces reflecting the inter-provincial socio-cultural differences in poverty. In addition, the factors that influence the number of poverty between provinces tend to differ depending on the socio-cultural conditions of the province concerned. It is proven by GWR that the variables affecting provincial poverty differ across provinces.

VII. SUGGESTION

The GWR model for the number of poor people in Indonesia can be modelled by different Kernel functions and Probability Distribution Function. In this study it is assumed that the probability distribution of number of poor people in indonesia had normal distribution.

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