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Using the *Geographically Weighted Regression (GWR) Method* to Find Out the Factors Causing Poverty in North Sumatra Province

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Abstract.*Poverty is a complex problem that affects various aspects of life in various regions. In this study, we use the Geographically Weighted Regression (GWR) method to identify factors that cause poverty in North Sumatra Province. This approach allows a more detailed analysis of the relationship between independent variables and poverty levels in each geographic location. We use socio-economic and spatial data to build GWR models and identify possible hidden patterns in the distribution of poverty. The findings from this research provide valuable insights for stakeholders to formulate more effective policies in overcoming poverty in North Sumatra Province.*

Keywords: *Poverty, Geographically Weighted Regression (GWR), North Sumatra Province, Factors Causing Poverty, Spatial Analysis.*

BACKGROUND

The background to this research is that poverty is a complex, multidimensional problem and covers various aspects. Due to its complexity, poverty alleviation requires programs that are integrated and do not overlap. The Central Statistics Agency (BPS) states that poverty is a measure of the minimum standard of living based on the amount of rupiah spent per capita/month to meet basic needs. Poverty is often seen as the inability to meet basic food and non-food needs as measured in terms of expenditure. In general, there are three indices used to measure the level of poverty, namely, poverty percentage, poverty depth index and poverty severity index.

There are several studies that discuss the *Geographically Weighted Regression* (GWR) method, including those conducted by Abdul and Kartiko (2019) to analyze poverty levels in Southeast Sulawesi Province, this research uses the 2017 Poverty Percentage. Research conducted by (Sukanto et al, 2019) on Spatial Analysis of Poverty Using the *Geographically Weighted Regression Approach* : Case Study of Pandeglang and Lebak Regencies. Research using the GWR method was also carried out by (Amalia & Sari, 2019) with the title Spatial Analysis to Identify Open Unemployment Levels Based on Regency/City on the Island of Java in 2017.

THEORETICAL STUDY

Poverty

Poverty is a condition when a person or group of people is unable to fulfill their basic rights to maintain and develop a dignified life. The factors that cause poverty used in this research are Population, Open Unemployment Rate (TPT), Gross Regional Domestic Product (GRDP), Human Development Index (HDI) and Minimum Wage.

Multiple Linear Regression

Multiple linear regression is a regression with two or more predictor variables and is an extension of simple linear regression. Multiple regression is useful for obtaining the influence between variables or looking for a functional relationship between two or more predictor variables and a response variable, or predicting two or more predictor variables with a response (Agustianto et al., 2018) . Equation model regression For observation lots with variable predictor as much so can written down in equality as following .

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \varepsilon_i \quad (1)$$

y_i : mark observation variable bound i

x_{ik} : mark observation variable free kth on observation i

β_0 : mark constant or *intercept* regression model

$\beta_{1,}\beta_{2,\cdots}\beta_k$: coefficient regression variable explainer to - *k*

ε_i : error on the i-th observation , assuming it is identical, independent and normally distributed with *a m*

Spatial Heterogeneity

Spatial heterogeneity refers to the existence of diversity in regional relationships. The spatial heterogeneity test was carried out to determine whether there were any characteristics or uniqueness at each observation location. The existence of spatial heterogeneity can produce different regression parameters at each observation location. Spatial heterogeneity can be identified using the *Breusch-Pagan test.*

Hypothesis used:

H_0: ${\sigma_1}^2 = {\sigma_2}^2 = \cdots = {\sigma_i}^2$(no spatial heterogeneity)

H_1: $minimal\ ada\ satu\ {\sigma_i}^2 \neq \sigma^2$(there is spatial heterogeneity)

Test statistics:

$$BP = \frac{1}{2}\boldsymbol{f}^T\boldsymbol{Z}(\boldsymbol{Z}^T\boldsymbol{Z})^{-\mathbf{1}}\boldsymbol{Z}^T\boldsymbol{f} \quad (2)$$

with factor elements$\boldsymbol{f}$ is $f_i = \frac{{e_i}^2}{\sigma^2} - 1$, which $e_i = y_i - \hat{y}_i$is obtained from the OLS method. $\boldsymbol{Z}$

is a sized matrix $n \times (p+1)$containing standardized normalized vectors for each observation.

Decision Area:

Reject H_0if the value $BP > x^2(p)$or if $P_{value} < \alpha$with p is the number of predictors.

Spatial Dependencies

Dependencies spatial happen consequence exists dependencies region . Dependencies spatial appear based on law Tobler I (1979) viz All something each other relate One with others , however something more near have great influence from on something far away . Test dependencies spatial done with use method *Moran's I*. *Moran's I* test was performed For see is observation in a location influential to observation at other locations located each other close by . Hypothesis used For *Moran's I* is as following :

H0 : I = 0 (no There is autocorrelation between room / location)

H_1 : $I \neq 0$ (exists autocorrelation between room / location)

Statistics test : $Z_{count} = \frac{I-E(I)}{\sqrt{var(I)}}$

with: $I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \boldsymbol{W}_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2}$ (3)

$$E(I) = I_0 = -\frac{1}{n-1} \quad (4)$$

$$var(I) = \frac{n^2 S_1 - nS_2 + 3S_0^2}{(n^2-1)S_0^2} - [E(I)]^2 \quad (5)$$

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} \boldsymbol{W}_{ij} \quad (6)$$

$$S_1 = \frac{1}{2}\sum_{i\neq j}^{n}\left(\boldsymbol{W}_{ji} + \boldsymbol{W}_{ij}\right)^2 \quad (7)$$

$$S_2 = \sum_{i=1}^{n}\left(\boldsymbol{W}_{ij} + \boldsymbol{W}_{ji}\right)^2 \quad (8)$$

Where :

Z_{count} : mark *Moran's I* test statistic

E(I) : value expectation from *Moran's I*

var (I) : value variance from *Moran's I*

e : Regression residuals *Ordinary Least Square* (OLS)

W : Matrix Weighter spatial

Decision area : H_0 is rejected If $|Z_{hitung}| > Z_{\alpha/2}\ atau\ P - value < \alpha$which means there are spatial dependencies between locations.

Geographically Weighted Regression (GWR)

Geographically Weighed Regression (GWR) is a method used to process spatial data. *Geographically Weighed Regression (GWR)* is a development of multiple linear regression analysis by providing different weightings for each observation location. According to

Fotheringham, et al (2002) GWR is a statistical method used to analyze spatial heterogeneity. The GWR model produces local model parameter estimators for each point or location where the data is observed. In the GWR model, the dependent variable y is estimated with predictor variables whose respective regression coefficients depend on the location where the data is observed. The GWR model can be written as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \qquad i = 1,2, \dots, n \tag{9}$$

with :

y_i : observation value of the *i -th response variable*

β_0 : constant or intercept at the i-th observation

(u_i, v_i) : geographic coordinates (*longitude, latitude*) of the location *i* -th observation

$\beta_k(u_i, v_i)$: observation value of the kth predictor variable *at the ith* observation location

x_{ik} : observation value of the kth predictor variable *at the ith* observation location

ε_i : *error of the 1st* observation which is assumed to be identical, independent and normally distributed with zero mean and constant varianceσ^2

(Caraka & Yasin, 2017).

The method for estimating GWR model parameters is to use the *Weighted Least Square (WLS) method* , namely by giving different weights to each location where the data is collected. For example, if the weighting for each location i is $\boldsymbol{W}(u_i, v_i)$then the location parameters $(u_i, v_i)$are estimated by adding the weighting elements and then minimizing the following sum of squared errors:

$$\sum_{j=1}^{n} \boldsymbol{W}(u_i, v_i)\, \boldsymbol{\varepsilon_i}^2 = \sum_{j=1}^{n} \boldsymbol{W}\,(u_i, v_i)\big[y_i - \beta_0(u_i, v_i) - \beta_1(u_i, v_i)x_{j1} - (u_i, v_i)x_{j2} - \cdots - \beta_k(u_i, v_i)x_{jk}\big]^2 \tag{10}$$

The solution to the above equation in matrix form is:

$$\boldsymbol{\varepsilon}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{\varepsilon} = [\boldsymbol{Y} - \boldsymbol{X\beta}(u_i, v_i)]^T \boldsymbol{W}(u_i, v_i)[\boldsymbol{Y} - \boldsymbol{X\beta}(u_i, v_i)]$$
$$= \boldsymbol{Y}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{Y} - \boldsymbol{YW}(u_i, v_i)\boldsymbol{X\beta}(u_i, v_i) - \boldsymbol{\beta^T}(u_i, v_i)\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{Y} + \boldsymbol{\beta}^T(u_i, v_i)\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{X\beta}(u_i, v_i) \tag{11}$$

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

$$\boldsymbol{\varepsilon}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{\varepsilon} = \boldsymbol{Y}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{Y} - \boldsymbol{2\beta}^T(u_i, v_i)\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{Y} + \boldsymbol{\beta}^T(u_i, v_i)\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{X\beta}(u_i, v_i) \tag{12}$$

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

$$\frac{\partial \boldsymbol{\varepsilon}^T \boldsymbol{W}(u_i,v_i)\boldsymbol{\varepsilon}}{\partial \boldsymbol{\beta}^T(u_i,v_i)} = 0 \tag{13}$$

$$-2X^T\boldsymbol{W}(u_i,v_i)\boldsymbol{Y} + 2\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X}\boldsymbol{\beta}(u_i,v_i) = 0 \tag{14}$$

$$\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X}\boldsymbol{\beta}(u_i,v_i) = \boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{Y} \tag{15}$$

To obtain $\widehat{\boldsymbol{\beta}}(u_i,v_i)$equation (2.26) above, multiply it by the inverse $\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X}$as follows

$$(\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X}\boldsymbol{\beta}(u_i,v_i) = (\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i) \tag{16}$$

so that the estimated GWR model parameters for each location are as follows:

$$\widehat{\boldsymbol{\beta}}(u_i,v_i) = [\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)\boldsymbol{Y} \tag{17}$$

Because there are n sample locations, this estimator is an estimate for each row of the local parameter matrix for all research locations. The matrix is:

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

with :

X : matrix of order$n \times (p+1)$

Y : matrix of order$n \times 1$

$\widehat{\boldsymbol{\beta}}(u_i,v_i)$: GWR parameter estimation vector

$\boldsymbol{W}(u_i,v_i)$: diagonal weighting matrix measuring $n \times n$each element i-th observation or expressed by $\boldsymbol{w}_{ij}$.

GWR Model Weighting

Spatial weighting is a weighting that explains the location of data from one another. The weighting of the GWR model is an important component, because this weighting value represents the location of the observation data from one another. The weighting scheme in GWR can use several different methods. One way is to use kernel functions. Kernel functions are used to estimate parameters in the GWR model. Several weighting functions formed from kernel functions consist of:

1. *Fixed Gaussian* Function

$$w_{ij}(u_i,v_i) = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right] \tag{18}$$

2. *Fixed Bisquare* Function

$$w_{ij}(u_i,v_i) = \begin{cases} \left(1-\left(\frac{d_{ij}}{h}\right)^2\right)^2 & ,untuk\ d_{ij} \le h \\ 0 & ,untuk\ d_{ij} > h \end{cases} \tag{19}$$

3. *Fixed Tricube* Function

$$w_{ij}(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^3\right)^3 & , untuk\ d_{ij} \le h \\ 0 & , untuk\ d_{ij} > h \end{cases} \quad (20)$$

with :

h : *non-negative* parameter which is called a smoothing parameter (*bandwidth*)

d_{ij} *Euclidean* distance between locations (u_i, v_i)defined as follows:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \quad (21)$$

(Agustianto, 2018).

RESEARCH METHODS

The type of research used is quantitative research. Quantitative research in this study uses secondary data obtained from publications by the Central Statistics Agency (BPS) of North Sumatra.

The steps taken to conduct this research are as follows:

1. Carrying out library studies by searching for and reading library materials that are relevant to the research topic in the form of books, journals or articles.
2. Conducting research at the Unimed library by collecting and inputting data about poverty and the factors that cause it in 2018.
3. After finding the research data, then describe the dependent variable (Y) and independent variable (X) that will be involved in forming the regression model.
4. Carry out modeling using multiple linear regression
5. Analyze the classic linear regression model with the following steps:
   a. Perform assumption tests (normality, multicollinearity, heteroscedasticity, and autocorrelation)
   b. Estimating multiple linear regression model parameters with OLS
   c. Test the significance of the multiple regression model (f test and t test).
6. Analysis of spatial influences using spatial heterogeneity and spatial dependency tests.
7. Analyzing poverty using *Geographically Weighted Regression (GWR) modeling* with steps:
   a. inputting poverty data in the districts/cities of North Sumatra Province in 2018
   b. Determine the coordinates of latitude *and longitude* in each district/city

(observation area)

c. Calculating the *Euclidean distance* between points in the observation area based on *latitude* and *longitude*
d. Determine the optimum *bandwidth* (best weighting) to be used in the GWR model based on the minimum *Cross Validation (CV) value* between the weighting functions
e. Calculate the weighting matrix at each observation location point
f. Estimating parameters for the GWR model with *Weighted Least Square* (WLS) at each observation location
g. testing the parameters of each GWR model simultaneously and partially

8. Drawing conclusions

RESULTS AND DISCUSSION

This research uses data on the percentage of poverty in North Sumatra Province in 2018. The locations used consist of 33 districts/cities. The variable used in this research is the dependent variable (Y) is the poverty percentage. Meanwhile the independent variables (X) are population (X_1), Open Unemployment Rate/TPT (X_2), Gross Regional Domestic Product/GRDP (X_3), Human Development Index/HDI (X_4) and Minimum Wage (X_5). Stages beginning before forming a *Geographically Weighted Regression* (GWR) model is regress percentage poverty in North Sumatra province with five variables independent . Model used is the *Ordinary Least Square* (OLS) model . Results Data processing from the OLS model with an alpha of five percent (α = 5%) shows that $F_{hitung} = 5.702 > F_{tabel} = 2.472$, meaning that there is at least one independent variable that has a significant influence on the response variable and vice versa. Apart from the F test, a partial test was carried out on the OLS model using the t test. Based on the results of this test with an alpha of five percent (α = 5%) it was found that the minimum wage variable (X_4) had a significant effect on the percentage of poverty in North Sumatra Province in 2018.

Test Assumption Classic

The normality test in this study used the *Kolmogorov-Smirnov Test method* . The test criteria carried out are if $\text{p} - value \geq \alpha$the data is normally distributed. Based on the Kolmogorov-Smirnov test , a value was obtained $\text{p} - value = 0{,}4336 > 0{,}05$which means the data is normally distributed. Furthermore done test multicollinearity by paying attention to the *Variance Influence Factor* (VIF) value. If the VIF value is > 10 then the data contains multicollinearity and vice versa. Results test this VIF on study This show that the data does not happen multicollinearity , because mark *VIF < 10* means that there is no strong linear relationship between the independent variables in the study.

Next, the Glejser test is carried out for show that data No fulfil assumption homoscedasticity . In research using the GWR method, the expected decision is that the regression model contains heteroscedasticity. By using the Glajser test It is obtained that $p_{value} = 0.0185 < \alpha = 0.05$, which means that a heteroscedasticity problem occurs. By Because That For analyze influential variables to percentage family almost poor in Island Regency /City Java will used GWR method .

Test Heterogeneity Spatial

The spatial heterogeneity test is needed in order to determine the existence of spatial diversity in observations. The existence of spatial heterogeneity can produce different regression parameters for each observation location. To identify the presence of spatial diversity, you can use the *Breusch-Pagan test.* The results of the analysis using the *Breusch-Pagan test* are as follows.

Table 1. *Breusch-Pagan test*

Breusch-Pagan (BP)	Df	p- *value*
11,937	5	0.03566

Based on the table above using the significance level $\alpha = 5\%$, it is obtained that $P_{value} = 0{,}03566 < \alpha = 0.05$. so it is concluded that there is spatial heterogeneity.

Test Dependencies Spatial

Spatial dependency occurs because of regional dependency. To analyze the presence or absence of spatial dependencies, *the Moran's I* test is used. *The Moran's I* test is used to identify a location from spatial grouping or spatial autocorrelation. Spatial autocorrelation is the correlation between variables based on space. The hypotosis used is

$H_0: I = 0$(no spatial autocorrelation)

$H_1: I \neq 0$(there is spatial autocorrelation)

Test statistics: $Z_{\text{hitung}} = \frac{I-E(I)}{\sqrt{var(I)}}$

$$= \frac{0{,}56959208-(-0{,}03125000)}{\sqrt{0{,}03919935}}$$

$$= \frac{0{,}60084208}{0{,}19788257}$$

$$= 3{,}036$$

Decision area: reject H $_0$ if $|Z_{hitung}| > Z_{\alpha/2}$ dan $P - value < \alpha$. Based on the analysis results, the value of $|Z_{hitung}| = 3{,}036 > Z_{(\frac{\alpha}{2})} = 1{,}96$ dan $P - value = 0{,}001204 < \alpha = 0{,}05$, which means there is spatial dependency between research locations, is obtained.

***Geographically Weighted Regression (GWR)* Modeling**

Following is map percentage pregnant poverty aspect spatial .

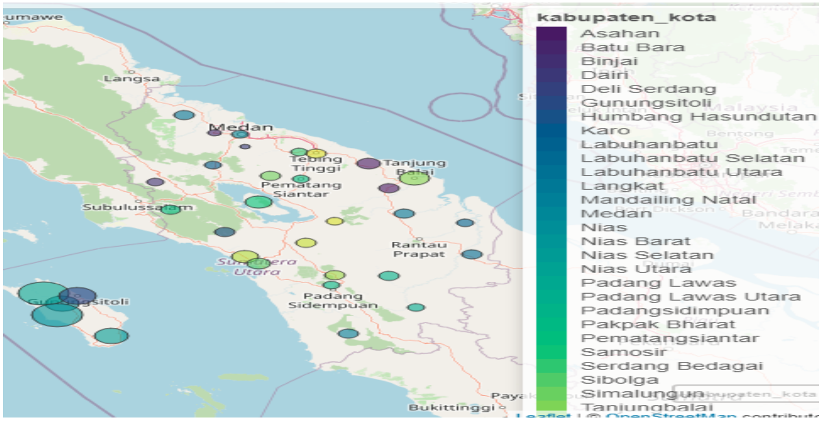

Figure 1. Poverty Percentage Map

Step First in modeling *Geographically Weighted Regression (GWR)* is count distance between location observation (distance *Euclidean)* based on line longitude and line latitude (latitude) each districts / cities in North Sumatra province .

Furthermore determine optimum *bandwidth* with use function weighter *fixed Gaussian.* The optimum *bandwidth* is determined from mark generating *bandwidth* minimum CV value . Obtained mark optimum *bandwidth* of 195.1136 with CV of 657.5274, p This show that area around region within a radius of 195.1136 ^{0} will considered own influence location . The more near region with area center will give more influence big . Furthermore do calculation matrix weighter For each location observation .

Then step furthermore is do GWR model parameter estimates for each location observation with use method *Weighted Least Square (WLS)* . Mark GWR model parameter estimates are obtained as following .

Table 2. Values GWR Model Parameter Estimation

Variable	Minimal	Median	Maximum	Global
Intercept	5.1926e+01	5.9723e+01	7.5354e+01	65.0428
x_1	-1.1960e-06	-8.1517e-07	-7.0521e-07	0.0000
x_2	1.4180e-01	2.8284e-01	3.5655e-01	0.2417
x_3	2.3138e-08	2.5920e-08	4.2166e-08	0.0000
x_4	-9.3306e-01	-7.0280e-01	-5.8282e-01	-0.7695

x_5	-1.3808e-06	-8.0882e-07	-4.5905e-07	0.0000

CONCLUSIONS AND RECOMMENDATIONS

1. Conclusion

Based on the research that has been carried out, the author can draw the following conclusions:

1. Based on the data used in this research, aspects of spatial heterogeneity and spatial dependency are fulfilled so that the data in this research can be analyzed using the GWR method.
2. The results of the analysis show that the percentage characteristics of poverty are clustered. The areas classified as having the highest percentage are in the Nias Islands area.

2. Suggestion

In this research, the author used the *adaptive kernel Gaussian weighting function* , so that future researchers can use other weighting functions. It is hoped that future researchers will select other, more varied variables by conducting better studies regarding significant independent variables.

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