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GEOGRAPHICALLY WEIGHTED PANEL REGRESSION MODELING OF POVERTY RATES IN TROPICAL RAINFOREST AREAS OF KALIMANTAN

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ABSTRACT

When applied to spatial panel data, the Geographically Weighted Panel Regression (GWPR) model is a localized version of the linear regression model. The Fixed Effect Model (FEM) inside estimator is used as a global model in this investigation. The purpose of this research is to obtain a GWPR model and identify the variables that affect the proportion of the impoverished in 56 districts and cities located in Kalimantan's humid tropical forest region between 2019 and 2022. The Weighted Least Square (WLS) approach, which provides geographic weighting in addition to the Least Square method, is used for estimating the parameters of the GWPR model. The optimal weighting function chosen from the adaptive bisquare, adaptive tricube, and adaptive gaussian weightings is the spatial weighting function used in the GWPR model estimate in this work. For determining the ideal bandwidth, the Cross Validation (CV) criterion is applied. According to the study's findings, the optimal weighting function is adaptive gaussian, which yields the best GWPR model with a CV of 8.8740 at the lowest. The GWPR model parameters were tested, and the results showed that both local and global influences affect the percentage of the population living in poverty. The gross domestic product (GDP), the open unemployment rate, the average length of education, the number of workers, and life expectancy are local factors that affect the percentage of the poor; on the other hand, the number of workers is a global factor that affects the percentage of the poor.

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1. INTRODUCTION

A statistical technique for examining the relationship between one response variable and one or more predictor variables is regression analysis. The regression modeling commonly used is the linear regression model [1]. The linear regression model has extensive use across diverse domains, including social and economic sciences. Data in the social and economic fields can be found in the form of spatial panel data. Data from many surveys conducted at various times on the same cross-section unit are referred to as spatial panel data. Panel data cannot be modeled using the classical linear regression model because there are assumptions that are not met in the classical linear regression model, namely the autocorrelation assumption is not met. A more appropriate modeling for panel data is panel regression [2].

There are three panel regression models, namely the Common Effect Model (CEM), Random Effect Model (REM), and Fixed Effect Model (FEM) [2]. Panel regression is often found using spatial panel data. The influence given by the geographical aspect will vary at each observation location. Panel regression modeling is not suited for spatial panel data with spatial heterogeneity; instead, the Geographically Weighted Panel Regression (GWPR) model is the most appropriate model to use. A local panel regression model that considers spatial data is the GWPR model. In this study, the GWPR model will be used to analyze socioeconomic data, specifically poverty. Spatial panel data, in which the influence varies by region, is what constitutes poverty data. The GWPR model on the percentage of poor people is carried out to determine the factors that influence poverty, so that it can be considered in making policies [3]. Regencies/cities in Kalimantan Island have different conditions, so the factors that influence poverty will be different. Policies made by local governments in reducing poverty rates will differ according to the conditions and factors that influence poverty in the region [4]. Panel data regression analysis has been used in research on the same subject make a modeling of the percentage of poor people according to regencies/cities in East Kalimantan. The study's findings suggest that the FEM model is the most appropriate one to use when examining the percentage of poor people.

Poverty is defined as the inability to achieve fundamental human requirements such as food, shelter, clothes, health, and education. Poverty is frequently caused by a combination of variables, including natural resources, access to health care, and education in the area. Poverty-causing factors vary by region. According to the Central Bureau of Statistics, the percentage of impoverished people in Indonesia in September 2022 was 9.57%, up 0.03% from March 2022's 9.54%. The condition of the poor in Indonesia is not necessarily in line with the condition of the poor at the regional level, such as in Kalimantan. The percentage of poor people in the September 2022 period in 5 provinces on the island of Kalimantan is West Kalimantan Province at 6.81%, East Kalimantan Province at 6.44%, South Kalimantan Province at 4.61%, Central Kalimantan Province at 5.22%, and North Kalimantan Province at 6.86% [5]. Although the percentage of impoverished individuals on the island of Kalimantan is lower than that of impoverished individuals throughout Indonesia, the percentage of impoverished individuals in the provinces on the island is still rather high and varies. In order to identify the variables that impact poverty and take them into account when formulating policy, the GWPR model is used to data on the percentage of the population that is impoverished.

Based on the background description above, researchers are interested in conducting a study entitled "Geographically Weighted Panel Regression Modeling of The Percentage of Poor Population in Tropical Rainforest Areas of Kalimantan 2019-2022". The purpose of this research is to obtain a GWPR model from the data on Kalimantan's proportion of the impoverished population and to identify the factors that affect that percentage based on the GWPR model.

2. RESEARCH METHODS

2.1 Data and Data Sources

The variables used in this study are one response variable and five predictor variables. Data and data sources can be seen in **Table 1**.

Table 1. **Data and Data Sources**

Variable	Symbol	Variable Name	Type of Data	Unit
Response	$\boldsymbol{y}$	Percentage of Poor Population	Ratio	Percent (%)
	$\boldsymbol{x_1}$	Gross Regional Domestic Product	Ratio	Billion Rupiah
	$\boldsymbol{x_2}$	Unemployment Rate	Ratio	Percent (%)
Predictor	$\boldsymbol{x_3}$	Mean Years of Schooling	Ratio	Year
	$\boldsymbol{x_4}$	Number of Workforce	Ratio	Person
	$\boldsymbol{x_5}$	Life Expectancy	Ratio	Year

Source: Statistics Indonesia 2022

2.2 Regression Analysis

A statistical method for establishing the causal relationship between two variables is regression analysis. To ascertain how well-known predictor variables may impact the response variable's value, regression analysis is employed. Simple linear regression and multiple linear regression are two categories of linear regression models based on the quantity of predictor variables. A multiple linear regression model consists of one response variable plus many predictor variables, whereas a simple linear regression model only contains one response variable and one predictor variable. The linear regression model makes the assumptions that errors are normally distributed, have no autocorrelation, and have constant error variance **[6]**.

2.3 Non-Multicollinearity Detection

Multicollinearity is an assumption that indicates a strong linear relationship between predictor variables in a regression model. Multicollinearity detection can use the VIF value. A VIF value of more than 10 indicates a multicollinearity problem in the regression model. The VIF value can be found using the **Equation (1)**.

$$VIF_k = \frac{1}{1 - R_k^2}, \quad k = 1,2, \dots, p \tag{1}$$

where VIF_k is the VIF value of the k-th predictor variable and R_k^2 is the coefficient of determination of the model x_k which is regressed against other predictor variables **[7]**.

2.4 Fixed Effect Model (FEM)

FEM is a panel data regression model that assumes that the intercept coefficient values vary, but the slope value remains constant **[8]**. **Equation (2)** displays the FEM model's general form

$$y_{it} = \beta_{0_i} + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_p x_{itp} + \varepsilon_{it} \,; i = 1,2, \dots, n \,; t = 1,2, \dots, T \tag{2}$$

β_{0_i} each cross-section unit's intercept coefficient value varies, as shown by **Equation (2)**. The inside estimator approach is used to alter β_{0_i} in order to do the FEM model parameter estimator. The actual cross-section data is subtracted from the average of the corresponding time series on the actual time series data to generate the within estimator technique. Creating an average model based on **Equation (2)** at each $t = 1,2,\dots,T$ is the first step in using the inside estimator approach. This gives you the cross-section equation in **Equation (3)**.

$$\bar{y}_i = \beta_{0_i} + \beta_1 \bar{x}_{i1} + \beta_2 \bar{x}_{i2} + \cdots + \beta_p \bar{x}_{ip} + \bar{\varepsilon}_{it} \;\, ; i = 1,2, \dots, n \tag{3}$$

Where

$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \,, \bar{x}_{ik} = \frac{1}{T}\sum_{t=1}^{T} x_{itk} \,, \bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it} \;\, ; k = 1,2, \dots, p \tag{4}$$

Equation (5) yields the FEM inside the estimator model when **Equation (3)** is subtracted from averages in **Equation (4)**.

$$y_{it}^* = \beta_1 x_{it1}^* + \beta_2 x_{it2}^* + \cdots + \beta_p x_{itp}^* + \varepsilon_{it}^* \,; \; i = 1,2, \dots, n; \; t = 1,2, \dots, T \tag{5}$$

Where

$$y_{it}^* = (y_{it} - \bar{y}_i),\ \ x_{itk}^* = (x_{itk} - \bar{x}_{ik}),\ \varepsilon_{it}^* = (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (6)$$

The data resulting from the transformation of **Equation (6)** is called demean data **[9]**.

2.5 Testing the Significance of FEM Model Parameters

1. Simultaneous Test

   The simultaneous test aims to determine the influence of predictor variables simultaneously on the response variable. The hypothesis of the simultaneous test is

   H_0 : $\beta_1 = \beta_2 = \cdots = \beta_p = 0$

   (Simultaneously the predictor variables do not affect the response variable)

   H_1 : at least there is one $\beta_k \neq 0$; $k = 1,2, \ldots, p$

   (There is at least one predictor variable that influences the response variable)

   The test statistics used in the simultaneous test of the FEM model can be seen in the **Equation (7)**

$$F_1 = \frac{MSReg}{MSE} \quad (7)$$

   where MSReg is the Mean Square of Regression and MSE is the Mean Square of Error. The critical region for the simultaneous test of the FEM model is to reject H_0 at a significant level if the value $F_1 > F_{(p;nT-n-p)}$ or if $p\ value < \alpha$ **[10]**.

2. Partial Test

   The partial test aims to determine the influence of each k-th predictor variable on the response variable. The partial test hypothesis is

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

   (There is no influence of the k predictor variable on the response variable).

   H_1 : $\beta_k \neq 0$; $k = 1,2, \ldots, p$

   (There is an influence of the k predictor variable on the response variable)

   The test statistics used in the partial test of the FEM model can be seen in **Equation (8)**

$$T_k = \frac{\hat{\beta}_k}{se(\hat{\beta}_k)},\ \ k = 1,2, \ldots, p \quad (8)$$

   where $se(\hat{\beta}_k)$ is standard error of the estimator β_k. The critical region for the partial test of the FEM model is to reject H_0 at a significant level if the value $|T_k| > t_{\left(\frac{\alpha}{2};(nT-p)\right)}$ or if p-value $< \alpha$ **[11]**.

2.6 Homoscedasticity Assumption Testing

The FEM model assumes that the variance of the error must have a constant value or homoscedasticity. Non-constant error variance or heteroscedasticity can cause inefficient parameter estimation and the conclusions obtained are considered not to be able to represent the actual conditions. The homoscedasticity assumption test can use the Glejser test. The hypothesis used is

H_0 : $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$

(There is no heteroscedasticity in the regression model)

H_1 : at least there is one $\sigma_i^2 \neq \sigma^2$; $i = 1,2, \ldots n$

(Heteroscedasticity occurs in the regression model)

The test statistics for the Glejser test can be seen in the **Equation (9)**

$$\mathrm{F}_2 = \frac{\left(\widehat{\boldsymbol{\varphi}}^{\mathrm{T}}\mathbf{X}^{\mathrm{T}}\boldsymbol{\varepsilon} - n\bar{\varepsilon}^2\right)/p}{\left(\boldsymbol{\varepsilon}^{\mathrm{T}}\boldsymbol{\varepsilon} - \widehat{\boldsymbol{\varphi}}^{\mathrm{T}}\mathbf{X}^{\mathrm{T}}\boldsymbol{\varepsilon}\right)/(nT - n - p)} \tag{9}$$

where $\widehat{\boldsymbol{\varphi}}$ is vector of parameter estimates and $\boldsymbol{\varepsilon}$ is vector of errors. The critical region for the Glejser test is to reject H_0 at a significant level if the value $F_2 > F_{(p;nT-n-p)}$ or if the p-value $< \alpha$ where n is the number of observation locations, T the number of observation times and p the number of independent variables **[12]**.

2.7 Spatial Weighting Function

The role of spatial weighting is very important because the weighting value will represent the location of the observation data from one to another. Spatial weighting will show the magnitude of the influence of the weighting value on the data at each location. One method used to calculate the magnitude of the spatial weighting is to use the adaptive *kernel* function. In this study, the kernel functions used are adaptive kernel bisquare, adaptive kernel tricube, and adaptive kernel Gaussian. The kernel function can be calculated using the Euclidean distance (d_{ij}) and bandwidth (smoothing parameter). One method for determining the optimum bandwidth uses the Cross Validation (CV) method. The CV value is calculated using the **Equation (10)**

$$\mathrm{CV} = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(h_i)]^2 \tag{10}$$

where $\hat{y}_{\neq i}(h_i)$ is the estimated value for y_i with observation data at i-th location not included in the parameter estimation **[13]**.

2.8 Geographically Weighted Panel Regression Model

When applied to spatial panel data, the GWPR model is a local regression model of the FEM inside estimator model. The FEM within estimator model is a global regression in the context of GWPR, namely a model that has the same parameter values at each observation location. **Equation (11)** shows the GWPR model at the to-i observation location and time to-t based on the FEM inside estimator model.

$$\begin{gathered} y_{it}^* = \beta_1(u_i,v_i)x_{it1}^* + \beta_2(u_i,v_i)x_{it2}^* + \cdots + \beta_p(u_i,v_i)x_{itp}^* + \varepsilon_{it}^* \\ i = 1,2,\ldots,n \\ t = 1,2,\ldots,T \end{gathered} \tag{11}$$

The GWPR model parameters are estimated using the WLS approach, which is based on minimizing the sum of squares with spatial weighting. **Equation (12)** can be used to produce the GWPR model estimator

$$\widehat{\boldsymbol{\beta}}(u_i,v_i) = \left(\mathbf{X}^{*\mathrm{T}}\mathbf{W}(u_i,v_i)\mathbf{X}^*\right)^{-1}\mathbf{X}^{*\mathrm{T}}\mathbf{W}(u_i,v_i)\mathbf{y}^* \tag{12}$$

with

$\boldsymbol{W}(u_i,v_i) = diag[w_{i1}(u_i,v_i)\ \ w_{i2}(u_i,v_i)\ \ \ldots\ \ w_{in}(u_i,v_i)]$ **[14]**.

2.9 GWPR Model Suitability Testing

The GWPR model's suitability for use with the global panel regression model is tested in the following step of analysis, which comes after parameter estimation. The model appropriateness test's hypothesis is

H_0 : $\beta_k(u_i,v_i) = \beta_k,\ i = 1,2,\ldots,n\,;\ \ k = 1,2,\ldots,p$

(There is no significant difference between the FEM panel regression model and the GWPR model)

H_1 : at least there is one $\beta_k(u_i,v_i) \neq \beta_k$

(There are significant differences between the panel regression model and the GWPR model)

The test statistics for the model suitability test can be seen in the Equation (13)

$$F_3 = \frac{JKG_G(H_0)/db_1}{JKG_G(H_1)/db_2} \quad (13)$$

where $JKG_G(H_0)$ is the sum of the squares of the errors below H_0 (based on the FEM model) and $JKG_G(H_1)$ is the sum of the squares of the errors under H_1 (based on the GWPR model). The critical area for the GWPR model suitability test is to reject H_0 at a significant level if the value $F_3 > F_{db_1;db_2}$ or if the p-value $< \alpha$ [15].

2.10 Partial Test of GWPR Model

The partial test aims to determine the influence of each k-th predictor variable on the response variable. The partial test hypothesis is

$H_0 : \beta_k(u_i, v_i) = 0 ; i = 1,2, \dots, n ; k = 1,2, \dots, p$

(There is no influence of the k predictor variable on the response variable)

$H_1 : \beta_k(u_i, v_i) \neq 0 ; i = 1,2, \dots, n ; k = 1,2, \dots, p$

(There is an influence of the k predictor variable on the response variable)

The test statistics used in the partial test of the GWPR model can be seen in Equation (14)

$$T_{k(u_i,v_i)} = \frac{\hat{\beta}_k(u_i, v_i)}{\hat{\sigma}\sqrt{c_{kk}}} \quad (14)$$

where c_{kk} is the k-th diagonal element from matrix $\mathbf{C}^T\mathbf{C}$ with $\mathbf{C} = \left(\mathbf{X}^{*T}\mathbf{W}(u_i, v_i)\mathbf{X}^*\right)^{-1}\mathbf{X}^{*T}\mathbf{W}(u_i, v_i)$ and $\hat{\sigma} = \sqrt{\frac{JKG_G(H_1)}{\delta_1}}$. The critical region for the partial test of the GWPR model is to reject H_0 at a significant level if the value $\left|T_{k(u_i,v_i)}\right| > t_{\frac{\alpha}{2}, \frac{\delta_1^2}{\delta_2}}$ or if p-value $< \alpha$ with $\delta_1 = tr\left((\mathbf{I} - \mathbf{L}^*)^T(\mathbf{I} - \mathbf{L}^*)\right)$ dan $\delta_2 = tr\left((\mathbf{I} - \mathbf{L}^*)^T(\mathbf{I} - \mathbf{L}^*)\right)^2$ [16].

3. RESULTS AND DISCUSSION

3.1 Data Description

The description for the research variables consists of the average, minimum value, and maximum value which can be seen in Table 2.

Table 2. Description of Data Observation

Variable	Year	Average	Min.	Max.
Percentage of Poor Population (y)	2019	6.0680	2.420	12.380
	2020	5.970	2.550	12.040
	2021	6.2980	2.890	12.010
	2022	6.0540	2.450	11.550
Gross Regional Domestic Product (x_1)	2019	16425	1768	126272
	2020	16066	1764	120954
	2021	16586	1786	124197
	2022	17400	1802	128805
Unemployment Rate (x_2)	2019	4.2590	1.710	9.060
	2020	4.9570	2.240	12.360
	2021	4.9530	2.300	12.380
	2022	4.5110	1.330	9.920
Mean Years of Schooling (x_3)	2019	8.2320	6.000	11.510
	2020	8.3210	6.010	11.520
	2021	8.4080	6.020	11.530
	2022	8.4940	6.210	11.550

Variable	Year	Average	Min.	Max.
Number of Workforce (x_4)	2019	145098	13203	428353
	2020	148994	14181	429093
	2021	151186	14848	428395
	2022	152117	14205	424229
Life Expectancy (x_5)	2019	70.520	63.580	74.410
	2020	70.630	63.830	74.490
	2021	70.760	64.10	74.760
	2022	70.960	64.530	74.780

Based on **Table 2**, for the response variable, the average percentage of poor people in 2019 on the island of Kalimantan was 6.0680%. The highest percentage of poor people in 2019 on the island of Kalimantan was 12.380% and the lowest in 2019 on the island of Kalimantan was 2.420%. The average percentage of poor people in 2020 on the island of Kalimantan decreased from the previous year to 5.9700%. The highest percentage of poor people in 2020 on the island of Kalimantan was 12.040% and the lowest in 2020 on the island of Kalimantan was 2.550%. The average percentage of poor people in 2021 on the island of Kalimantan increased from the previous year to 6.2980%. The highest percentage of poor people in 2021 on the island of Kalimantan was 12.010% and the lowest in 2021 on the island of Kalimantan was 2.890%. The average percentage of poor people in 2022 on the island of Kalimantan decreased again from the previous year to 6.0540%. The highest percentage of poor people in 2022 on the island of Kalimantan was 11.550% and the lowest in 2022 on the island of Kalimantan was 2.450%.

3.2 Non-Multicollinearity Detection

Finding a linear relationship between predictor variables and other predictor variables in the regression model is the goal of multicollinearity identification. **Equation (1)** is used to calculate the VIF value, and **Table 3** displays the results.

Table 3. **VIF Value**

Variable (x_k)	VIF_k	Detection Results
Gross Regional Domestic Product (x_1)	1.86006	There is no multicollinearity
Unemployment Rate (x_2)	1.63472	There is no multicollinearity
Mean Years of Schooling (x_3)	1.55729	There is no multicollinearity
Number of Workforce (x_4)	1.66218	There is no multicollinearity
Life Expectancy (x_5)	1.37351	There is no multicollinearity

It is clear from **Table 3** that none of the predictor variables' VIF values is greater than 10. Consequently, it can be said that the predictor variables in the regression model do not exhibit multicollinearity.

3.3 Panel Regression Test

A panel regression model consisting of three models, namely CEM, REM, and FEM will be selected to determine the best panel regression model. The selection of the best panel regression model is done using the Chow test and the Hausman test. The first test uses the Chow test to select the best regression model between CEM and FEM. The next test uses the Hausman test to select the best regression model between FEM and REM **[17]**. The results of the two tests can be seen in **Table 4**.

Table 4. **Panel Regression Test**

Testing	p-value	Selected Model
Chow test	$< 2.2 \times 10^{-16}$	FEM
Hausman test	0.00673	FEM

It is clear from **Table 4** that none of the Chow test or Hausman test value is greater than 0.05, so the be best panel regression model used is FEM.

3.4 FEM Model

The estimator model for the proportion of impoverished population data with five predictor variables, based on the general FEM within estimator model in **Equation (15)**, is

$$y_{it}^{*} = \beta_1 x_{it1}^{*} + \beta_2 x_{it2}^{*} + \beta_3 x_{it3}^{*} + \beta_4 x_{it4}^{*} + \beta_5 x_{it5}^{*} + \varepsilon_{it}^{*}\ ;\ i = 1,2,\ldots,56\ ;\ t = 1,2,3,4 \qquad (15)$$

The estimation of the FEM model parameters can be seen in **Table 5**.

Table 5. FEM Model Parameter Estimation

Parameter	Estimation
β_1	0.00001
β_2	0.00741
β_3	0.29580
β_4	-0.00001
β_5	0.08861

Based on the estimates in **Table 5**, the model formed is

$$\hat{y}_{it}^{*} = 0.00001x_{it1}^{*} + 0.00741x_{it2}^{*} + 0.29580x_{it3}^{*} - 0.00001x_{it4}^{*} + 0.08861x_{it5}^{*}$$
$$i = 1,2,\ldots,56$$
$$t = 1,2,3,4 \qquad (16)$$

3.5 Testing the Significance of FEM Model Parameters

Simultaneous parameter testing is carried out to determine the significance of the regression parameters on the response variables simultaneously. The hypothesis of simultaneous parameter significance testing is

$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$

(Simultaneously, Gross Regional Domestic Product, Unemployment Rate, Mean Years of Schooling, Number of Workforce, and Life Expectancy do not affect the Percentage of Poor Population in Kalimantan)

H_1 : at least there is one $\beta_k \neq 0\ ;\ k = 1,2,3,4,5$

(Simultaneously, Gross Regional Domestic Product, Unemployment Rate, Mean Years of Schooling, Number of Workforce, and Life Expectancy have an effect on the Percentage of Poor Population simultaneously.)

Based on the statistical value of the F_1 test calculated using **Equation (7)** and the p-value results can be seen in **Table 6**.

Table 6. Simultaneous Test Results of FEM Model

F_1	$F_{(0,05;5;163)}$	p-value	Decision
2.32453	2.26962	0.04523	Reject H_0

Based on **Table 6**, the test decision was obtained, namely rejecting H_0 at a significance level of 0.05. The conclusion of the simultaneous parameter significance test is that the variables Gross Regional Domestic Product, Unemployment Rate, Mean Years of Schooling, Number of Workforce, and Life Expectancy have a simultaneous effect on the Percentage of Poor Population in Kalimantan.

Partial parameter testing is used to determine the influence of each k-th predictor variable on the response variable partially. The hypothesis of partial parameter significance testing is

$H_0 : \beta_k = 0\quad ;\ k = 1,2,3,4,5$

(There is no influence of predictor variables x_k on the Percentage of Poor Population in Kalimantan Island)

$H_1 : \beta_k \neq 0\quad ;\ k = 1,2,3,4,5$

(There is influence of predictor variables x_k on the Percentage of Poor Population in Kalimantan Island)

Based on the statistic value test T_k which is calculated using **Equation (8)** and the p-value results can be seen in **Table 7**.

Table 7. FEM Model Partial Test Results

Variable	$\lvert T_k \rvert$	p-value	Decision
Gross Regional Domestic Product (x_1)	0.41940	0.67548	Failed to reject H_0
Unemployment Rate (x_2)	0.23120	0.81745	Failed to reject H_0
Mean Years of Schooling (x_3)	1.10880	0.26916	Failed to reject H_0
Number of Workforce (x_4)	3.22780	0.00151	Reject H_0
Life Expectancy (x_5)	0.48250	0.63011	Failed to reject H_0

Table 7 led to the conclusion that, for the Number of Workforce variable, H_0 should be rejected at a significance level of 0.05. This is demonstrated by the predictor variable's p-value being less than the value α = 0.05 and the results of the statistical test T_k having a value larger than the value $t_{(0,025;219)}$ = 1.97086. The percentage of Kalimantan Island's poor population is partially influenced by the Number of Workforce variable, according to the results of the parameter significance test.

3.6 Homoscedasticity Assumption Testing

One of the assumption tests carried out on the FEM within estimator model is the homoscedasticity test. The hypothesis of the homoscedasticity test is

$H_0 : \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \cdots = \sigma_{56}^2 = \sigma^2$

(The error variance is constant across all observation locations)

H_1 : at least there is one $\sigma_i^2 \neq \sigma^2$; $i = 1,2,3, \ldots, 56$

(The error variance is not constant across all observation locations.)

Based on the test statistic value F_2 which is calculated using **Equation (9)** and the p-value results can be seen in **Table 8**.

Table 8. FEM Model Homoscedasticity Test Results

F_2	$F_{(0,05;5;163)}$	p-value	Decision
2.29473	2.26962	0.04776	Reject H_0

Based on **Table 8**, the test decision was obtained, namely rejecting H_0 at a significance level of 0.05 The homoscedasticity assumption of the FEM inside estimator model is not met, according to the homoscedasticity test's conclusion, which is that the error variance is not constant across all observation locations.

3.7 Spatial Weighting Function

Based on **Equation (10)**, the CV value calculated is obtained from each weighting function used, namely Adaptive Bisquare, Adaptive Tricube, and Adaptive Gaussian, which can be seen in **Table 9**.

Table 9. Weighting Function CV

Weighting Function	CV Value
Adaptive Bisquare	9.0081
Adaptive Tricube	8.9331
Adaptive Gaussian	8.8740

Based on the CV values in **Table 9**, it can be concluded that the best model is the GWPR model with the Adaptive Gaussian weighting function with a CV value of 8.8740.

3.8 GWPR Model

The model for the percentage of the population that is impoverished with five predictor variables is based on the general GWPR model found in **Equation (17)**.

$$y_{it}^* = \beta_1(u_i,v_i)x_{it1}^* + \beta_2(u_i,v_i)x_{it2}^* + \beta_3(u_i,v_i)x_{it3}^* + \beta_4(u_i,v_i)x_{it4}^* + \beta_5(u_i,v_i)x_{it5}^* + \varepsilon_{it}^*$$
$$i = 1,2,\dots,56$$
$$t = 1,2,3,4 \quad (17)$$

The GWPR model for the percentage of poor people was formed as many as 56 models, one of which was the model in Ketapang Regency, West Kalimantan Province.

$$\hat{y}_{48t}^* = -0.00055x_{48t1}^* - 0.07553x_{48t2}^* - 0.00202x_{48t3}^* + 0.00002x_{48t4}^* - 0.00206x_{t5}^*$$
$$t = 1,2,3,4 \quad (18)$$

where the model can be described by following **Equation (19)** as

$$(y_{48t} - \bar{y}_{48}) = \begin{array}{l} -0.00055(x_{48t1} - \bar{x}_{481}) - 0.07553(x_{48t2} - \bar{x}_{482}) - 0.00202(x_{48t3} - \bar{x}_{483}) \\ +0.00002(x_{48t4} - \bar{x}_{484}) - 0.00206(x_{48t5} - \bar{x}_{485}) \end{array} \quad (19)$$

Thus, it can be calculated by subtracting the average in **Equation (20)**

$$(y_{48t} - 10.0875) = \begin{array}{l} -0.00055(x_{48t1} - 18659.2175) - 0.07553(x_{48t2} - 6.3350) \\ -0.00202(x_{48t3} - 7.3775) + 0.00002(x_{48t4} - 241356.2500) \\ -0.00206(x_{48t5} - 71.1225) \end{array} \quad (20)$$

then the regression model obtained can be seen in the **Equation (21)**

$$\hat{y}_{48t} = \begin{array}{l} 16{,}83413 - 0{,}00055x_{48t1} - 0{,}07553x_{48t2} \\ -0{,}00202x_{48t3} + 0{,}00002x_{48t4} - 0{,}00206x_{48t5} \end{array}$$
$$t = 1,2,3,4 \quad (21)$$

3.9 Model Suitability Testing

The hypothesis testing of the model suitability aims to test the suitability of the GWPR model. The GWPR model's applicability is to be tested according to the hypothesis that

H_0 : $\beta_k(u_i,v_i) = \beta_k,\ i = 1,2,\dots,56\ ;\ \ k = 1,2,3,4,5$

(There is no significant difference between the FEM panel regression model and the GWPR model.)

H_1 : at least there is one $\beta_k(u_i,v_i) \neq \beta_k,\ \ i = 1,2,\dots,56\ ;\ \ k = 1,2,3,4,5$

(There are significant differences between the panel regression model and the GWPR model.)

Based on the statistical value of the F_3 test calculated using **Equation (13)** and the p-value results that can be seen in **Table 10**.

Table 10. Model Suitability Test Results

F_3	$F_{(0,05;5;163)}$	p-value	Decision
4.59490	1.27550	< 0.00001	Reject H_0

Based on **Table 10**, the test decision is obtained, namely rejecting H_0 at a significance level of 0.05. The conclusion of the GWPR model suitability test is that there is a significant difference between the panel regression model and the GWPR model.

3.10 Partial Test of GWPR Model

To ascertain the partial impact of each predictor variable on the response variable, partial parameter testing is employed. Based on the variables that influence the percentage of impoverished individuals displayed in the distribution map in **Figure 1**, the partial test results of the GWPR model in 56 districts/cities can be divided into 14 groups.

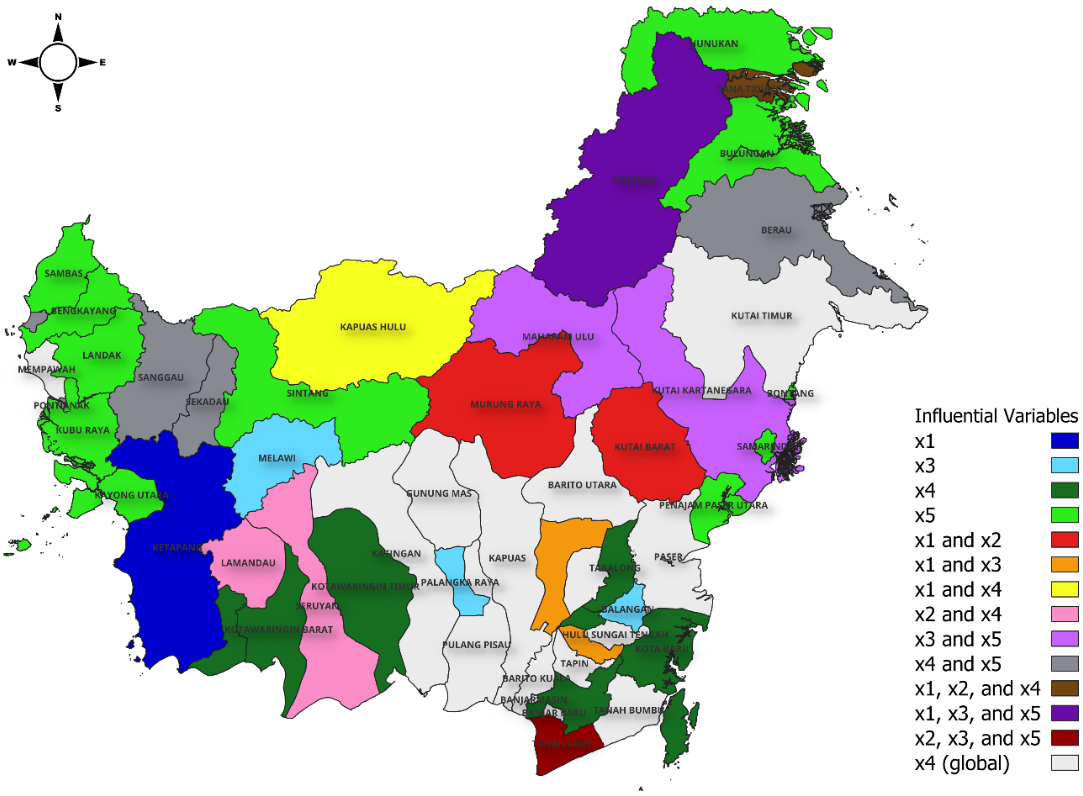

Figure 1. Grouping Based on Influential Variables

Based on **Figure 1**, it can be seen that the percentage of poor people in brown areas indicates that the influential variables are Gross Regional Domestic Product, Unemployment Rate, and Number of Workforce with the region, namely Tana Tidung Regency. The percentage of poor people in dark purple areas indicates that the influential variables are Gross Regional Domestic Product, Mean Years of Schooling, and Life Expectancy with the region, namely Malinau Regency. The percentage of poor people in dark red areas indicates that the influential variables are Unemployment Rate, Mean Years of Schooling, and Life Expectancy with the region, namely Tanah Laut Regency.

4. CONCLUSIONS

The conclusion obtained from this study is as following

1. Based on the GWPR model, the percentage of poor population produces 56 models for t=1,2,3,4. One of the GWPR models of Ketapang Regency is

   $$\hat{y}_{48t} = 16.8341 - 0.0006x_{48t1} - 0.0755x_{48t2} - 0.0020x_{48t3} + 0.00002x_{48t4} - 0.0021x_{48t5}$$

   This model tells us that based on the partial test in Figure 1, the variable that affects the percentage of poor people in the 48th location is the gross regional domestic product. The regression coefficient for the gross regional domestic product variable of -0.0006 states that every 1 billion rupiah increase in gross regional domestic product will reduce the percentage of poor people in Ketapang Regency by 0.0006%.

2. Based on the results of the partial parameter significance testing and Figure 1, the GWPR model in 56 districts/cities can be grouped into 14 groups according to the factors that influence the percentage of poor people, as follows

   a. The factors that influence the percentage of poor people in the first group of districts/cities are Gross Regional Domestic Product with local influencing factors.

   b. The factors that influence the percentage of poor people in the second group of districts/cities are Mean Years of Schooling with local influencing factors.

c. The factors that influence the percentage of poor people in the third group of districts/cities are the Number of Workforce with local influencing factors.

d. The factors that influence the percentage of poor people in the fourth group of districts/cities are Life Expectancy with local influencing factors.

e. The factors that influence the percentage of poor people in the fifth group of districts/cities are Gross Regional Domestic Product and Unemployment Rate with local influencing factors.

f. The factors that influence the percentage of poor people in the sixth group of districts/cities are Gross Regional Domestic Product and Mean Years of Schooling with local influencing factors.

g. The factors that influence the percentage of poor people in the seventh group of districts/cities are Gross Regional Domestic Product and Number of Workforce with local influencing factors.

h. Factors that influence the percentage of poor people in the eighth group of districts/cities are the Unemployment Rate and the Number of Workforce with local influencing factors.

i. Factors that influence the percentage of poor people in the ninth group of districts/cities are Mean Years of Schooling and Life Expectancy with local influencing factors.

j. Factors that influence the percentage of poor people in the tenth group of districts/cities are the Number of Workforce and Life Expectancy with local influencing factors.

k. Factors that influence the percentage of poor people in the eleventh group of districts/cities are Gross Regional Domestic Product, Unemployment Rate, and Number of Workforce with local influencing factors.

l. Factors that influence the percentage of poor people in the twelfth group of districts/cities are Gross Regional Domestic Product, Mean Years of Schooling, and Life Expectancy with local influencing factors.

m. Factors that influence the percentage of poor people in the thirteenth group of districts/cities are Unemployment Rate, Mean Years of Schooling, and Life Expectancy with local influencing factors.

n. The factor that influences the percentage of poor people in the fourteenth group of districts/cities is the Number of Workforce, with the influencing factor being global in nature.

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