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APPLICATION OF GEOGRAPHICALLY WEIGHTED REGRESSION FOR MODELING THE POVERTY CASES IN KALIMANTAN, INDONESIA

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ABSTRACT

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Poverty is one of the most global issues that remains a concern worldwide, including in Indonesia, so the government wants to decrease the national poverty rate, as outlined in the 2021-2024 National Medium-Term Development Plan. Unfortunately, the hope for a reduction in the poverty rate has not been achieved in several regions, such as in 4 out of 5 provinces in Kalimantan. Therefore, analyzing the factors causing poverty in the Kalimantan region is needed.

The purpose of the research is to analyze the factors causing poverty in Kalimantan region using the Geographically Weighted Regression Model in order to give clear information for the government to decrease the poor rate in this region.

GWR (Geographically Weighted Regression) is an extension of the regression method. The equation parameters for each observation location differ from one location to another. The weighting function used were fixed gaussian, fixed bisquare, fixed tricube, adaptive gaussian, adaptive bisquare, and adaptive tricube. The data used in this study are secondary data obtained from the Central Statistics Agency of West Kalimantan, Central Kalimantan, East Kalimantan, South Kalimantan, and North Kalimantan provinces.

Research found 17 different groups of cities with the same characteristics about factors affecting the percentage of poor people. Based on R^2 and AIC value, the best model is the model with fixed tricube function. The R^2 score is 0.8952, while the AIC score is 155.83, so the model can explain 89.52% of poverty percentage and about 10.48% of it should be explained by other variables. The GWR model is better than OLS or global regression model. Thus, spatial analysis to see the factors affecting the percentage of poor people in each regency and city in Kalimantan, Indonesia has been successfully carried out.

This research only used nine independent variables which are expected to be factors causing poverty percentage. The next research can add more variables to increase the R^2.

This research analyzes factors causing poverty percentage in each city of Kalimantan region, which have never been done in another research. Besides, it was found that there are cities from different province who have the same factors affecting the poverty. That will be an interesting point to deep the reason why a city has same characters with city in another province.

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1. INTRODUCTION

Poverty is a serious global issue that remains a concern worldwide. This is because poverty is a multidimensional problem involving various social, economic, educational aspects, and leading to various other issues such as rising crime rates, environmental pollution, hunger, and poor health and nutrition status [1]. This interconnected chain must be broken, one way being the elimination of poverty as outlined in the first Sustainable Development Goal pursued by all countries, including Indonesia [2].

Indonesia is the world's largest archipelagic country with the fourth-largest population after China, India, and the United States [3]. Unfortunately, Indonesia is also among the 100 poorest countries in the world, ranking 73rd [4]. The high poverty rate in Indonesia has prompted the government to implement various programs to alleviate poverty. In addressing extreme poverty, the government issued Presidential Instruction Number 4 to accelerate the eradication of extreme poverty in Indonesia, aiming to achieve zero percent extreme poverty by 2024 [5, 6].

The government not only targets a reduction in extreme poverty but also a decrease in the national poverty rate, as outlined in the 2021-2024 National Medium-Term Development Plan, with the expected percentage of poor people in Indonesia in 2024 being 6.5 to 7 percent [7]. As of now, government programs can be considered successful as the poverty rate has decreased from 9.71 percent in 2021 to 9.57 percent in 2022 [8]. Unfortunately, the hope for a reduction in the poverty rate has not been achieved in several regions, such as in 4 out of 5 provinces in Kalimantan. If the percentage of poor people in Indonesia decreases, the percentage in Kalimantan actually increases from 5.845 percent in 2021 to 5.898 percent in 2022 [9].

The Increase in the poverty rate in the Kalimantan region needs attention from both the provincial governments in Kalimantan and the central government. Various poverty alleviation programs will work optimally when the causes of poverty in a region are clearly understood. In the research by Priseptian and Primandhana (2022), an analysis of the factors causing poverty was conducted using multiple regression involving independent variables such as provincial minimum wage, human development index, economic growth, and unemployment [10]. However, the multiple regression analysis method cannot map different factors in each region [11]. Therefore, the analysis of factors causing poverty in the Kalimantan region is conducted using the Geographically Weighted Regression model. The varying geographic conditions in the Kalimantan region will certainly affect the condition of natural resources, human resources, access to technology, and various other aspects. Through the Geographically Weighted Regression model, the spatial heterogeneity that is typically considered an error in global regression becomes a weighting function that distinguishes the conditions of each region [12]. Thus, the factors influencing the poverty rate in each regency/city in the Kalimantan region can be depicted more clearly and comprehensively.

2. METHODS

Material and Data

The data used in this study are secondary data obtained from the Central Statistics Agency of West Kalimantan, Central Kalimantan, East Kalimantan, South Kalimantan, and North Kalimantan provinces. The dependent variable analyzed is the percentage of the poor population (Y). Meanwhile, the independent variables used are population density (X_1), literacy rate in Latin script (X_2), the number of non-labor force (X_3), percentage of own residential houses (X_4), the percentage of households with a floor area < 19 m² (X_5), the percentage of the population aged 5 years and over with mobile phones (X_6), the percentage of the population aged 5 years and over with internet access (X_7), the percentage of the population accessing the internet from the workplace (X_8), and the percentage of households with PLN electricity as the source of lighting (X_9).

Research Method

In analyzing the percentage of the poor population on the island of Kalimantan, this research uses the Geographically Weighted Regression (GWR) model with Gaussian Kernel, Bi-Square, and Tricube as weighting functions. Selection of Gaussian and Bisquare functions is because both of them use continuous values so that the result analysis will be better, while the tricube function is used because it is flexible with the data patterns being analyzed [13, 14].

2.1 Regression Model

Regression analysis pertains to the study of the dependency of one variable, which is the dependent variable, on one or more independent variables. Multiple linear regression is a method that models the relationship between the dependent variable (y) and the independent variables $(x_1, x_2, \dots, x_m)$ [15]. The general model for multiple linear regression with p independent variables is [16]:

$$y_i = \beta_0 + \sum_{q=1}^{p} \beta_q x_{iq} + \varepsilon_i, i = 1,2, \dots, n$$

y_i	:	The value of the dependent variable on the i-th observation
x_{iq}	:	value of the q-th independent variable at the i-th observation
β_0	:	intercept of regression model
β_q	:	$q - th$ independent variable regression coefficient
ε_i	:	Error in the $i - th$ observation

2.2 Spatial Data

Spatial data is data that can provide detailed information about specific locations and can be represented using a coordinate system [17]. There are two essential aspects that differentiate spatial data from other data, namely, location information in terms of coordinates (latitude and longitude) and descriptive information (attributes) or non-spatial information related to the location. A statistical method for addressing issues related to regression while considering geographic location is Geographically Weighted Regression.

2.3 Geographically Weighted Regression (GWR)

The GWR (Geographically Weighted Regression) model is an extension of the regression method. However, in the GWR model, the equation parameters for each observation location differ from one location to another [18]. In GWR analysis, the model generated cannot be used to predict parameters other than those at the observation location [19]. There are several differences between global regression and GWR, including [13]:

Table 1. Difference between global regression and GWR

	Global Regression	GWR
Parameter value	Same for each location	Different for each location
Statistics value	One	As many as location number
GIS	Not exist	Exist
Spatial factor	Not noticed	Noticed

GWR models can also be written mathematically, namely [16] :

$$y_i = \beta_0(u_i, v_i) + \sum_{q=1}^{p} \beta_q(u_i, v_i)x_{iq} + \varepsilon_i, i = 1,2,\dots,n$$

y_i	:	The value of the dependent variable on the i-th observation
x_{iq}	:	value of the q-th independent variable at the i-th observation
$\beta_0(u_i, v_i)$	:	Model intercept value at i-th location
$\beta_q(u_i, v_i)$	:	q-explanatory variable regression parameter value for each i-th location
(u_i, v_i)	:	Coordinate point (latitude, longitude) of the i-th location
ε_i	:	Error in the i-th observation

2.4 Assumption Test

Testing classical assumptions before hypothesis testing is one of the conditions that must be met in quantitative research. Test the assumptions used as follows:

2.4.1 *Normality Test*

Normality test is used to determine whether the residuals are normally distributed or not. There are several statistical tests that can be employed for normality testing, such as Shapiro-Wilk, Anderson-Darling, and Kolmogorov-Smirnov. If the p-value is greater than the significance level alpha, then the residual data is normally distributed [20].

2.4.2 *Multicollinearity Test*

This test is used to examine whether there is a high correlation between independent variables in a multiple linear regression model [21]. A good regression model should not have correlations among the independent variables [22]. There are several ways to assess the presence of multicollinearity, including *Correlation values among independent variables* (should be below 0.5) and the Variance Inflation Factor (VIF) score (should be more than 10) [23].

2.4.3 *Autocorrelation Test*

The autocorrelation test aims to test whether in the linear regression model there is a correlation between usage errors in period t with confounding errors in period t-1 (previously) [24]. If the p-value is greater than the significance level, then there is no autocorrelation in the global regression model [25].

2.4.4 *Heteroscedasticity Test*

Heteroscedasticity problem is usually checked by using Breusch-Pagan test. This test is used to see if the residuals from the formed model have homogeneous variance or not [26]. In linear regression, the variance of the data must be homogeneous, but in GWR analysis the variance value must be heterogeneous, which means that it shows spatial diversity in the data [27]. A p-value greater than the significance level indicates that variance is homogeneous [28].

2.4.5 *Moran Index*

The Moran's Index is an analytical technique used to test for the presence of autocorrelation with location-based covariates [29]. A smaller p-value compared to the significance level indicates the absence of spatial autocorrelation in the data [30].

2.5 Optimum Weighting and Bandwidth Selection

Bandwidth selection process use the weighting function, named Kernel function. There are two types of weighting function for bandwidth, those are fixed and adaptive.

2.5.1 *Fixed Kernel*

Fixed kernel functions have the same bandwidth at each point of observation location. The three types of kernels used in GWR are [31] :

Fixed Gaussian

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right]$$

Fixed Bi-Square

$$w_{ij} = \begin{cases} \left[1-\left(\frac{d_{ij}}{b}\right)^2\right]^2, & \text{if } d_{ij} < b \\ 0, & \text{others} \end{cases}$$

Fixed Tricube

$$w_{ij} = \begin{cases} \left[1-\left(\frac{d_{ij}}{b}\right)^3\right]^3, & \text{if } d_{ij} < b \\ 0, & \text{others} \end{cases}$$

2.5.2 *Adaptive Kernel*

Adaptive kernel functions have different bandwidth at each observation location point. The three types of kernels used in GWR are [31] :

Adaptive Gaussian

$$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b_{i(k)}}\right)^2\right]$$

Adaptive Bi-Square

$$w_{ij} = \begin{cases} \left[1-\left(\frac{d_{ij}}{b_{i(k)}}\right)^2\right]^2, & if \ d_{ij} < b \\ 0, & others \end{cases}$$

Adaptive Tricube

$$w_{ij} = \begin{cases} \left[1-\left(\frac{d_{ij}}{b_{i(k)}}\right)^3\right]^3, & if \ d_{ij} < b \\ 0, & others \end{cases}$$

$b_{i(k)}$ is the adaptive bandwidth that specifies k as the closest location distance from the i-th observation location point.

The selection of the optimal bandwidth in Geographically Weighted Regression (GWR) is crucial because it will affect the model's accuracy with respect to the data. A small bandwidth value will result in parameter estimation at the i-th observation location becoming increasingly dependent on the closest neighboring observation locations to the i-th location, thereby increasing the generated variance [32]. Conversely, if the bandwidth value is very large, it will lead to increasing bias, causing the obtained model to be overly smooth [33].

One of the methods that can be used to determine the optimal bandwidth is cross-validation (CV). The optimal bandwidth is the bandwidth that yields the minimum CV value, calculated with the following formula [34]:

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

2.6 Parameter Estimator of GWR Model

The estimation of parameter $\beta_{(u_i,v_i)}$ at the i-th location can be carried out using the Weighted Least Squares (WLS) method [35]. In parameter estimation at a specific location, the WLS method assigns different weights to all observations. The magnitude of these weights is based on the distance between observation locations. The closer the distance to the location whose parameter is being estimated, the greater the weight in estimating $\beta_{(u_i,v_i)}$ [36]. The GWR model parameter estimator is obtained as follows [12]:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y$$

2.7 The Best Model Determination

The best model is determined based on the highest *coefficient determination* ($\boldsymbol{R^2}$) and the lowest *Akaike Information Criterion* (AIC). In GWR, R^2 can be determined using the following equation [37]:

$$R_i^2 = \frac{SSR_{GWR}}{SST_{GWR}} = \frac{SST_{GWR} - SSE_{GWR}}{SST_{GWR}}$$

While the AIC value can be determined through the following calculation [38].:

$$AIC = 2n\,log(\hat{\sigma}) + n\,log(2\pi) + n + tr\,(S)$$

3. RESULTS

3.1 Data Exploration

Descriptive statistics that depict the percentage of the impoverished population as the dependent variable and the influencing independent variables can be observed in Table 2.

Table 2. Statistic Descriptive

Variable	Min	Max	Mean
Y	2.45	11.55	6.054
X_1	2	6785.49	382.03
X_2	88.57	99.82	96.94
X_3	5920	249607	73905
X_4	20.72	93.64	80.55
X_5	0	5.61	1.628
X_6	51.97	88.46	71.66
X_7	43.25	88.28	68.43
X_8	6.72	38.42	24.09
X_9	57.98	100	90.62

Table 2 shows that each variable has different range. Several variables have a wide range of values, such as X_3 (the number of non-labor force) and X_1 (population density). In the opposite, some variables have a small range, such as X_5 (percentage of households with a floor area < 19 m^2), X_8 (percentage of the population accessing the internet from the workplace), and Y (percentage of poor population) itself.

3.2 Global Regression Assumption

3.2.1 *Multicollinearity*

Table 3. Multicollinearity Test

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
VIF	1.49	1.99	1.50	1.81	1.26	7.55	8.32	1.78	1.76

Multicollinearity is assumed to occur when the VIF (Variance Inflation Factor) value is greater than 10. Since the VIF for each independent variable is less than 10, it is concluded that there is no multicollinearity in the data.

3.2.2 *Autocorrelation*

The symptoms of autocorrelation can be identified by conducting a Durbin-Watson test. Based on the analysis, a Durbin-Watson test statistic of 1.796 was obtained with a p-value of 0.266. The p-value is greater than the significance level used (alpha = 0.05), so it is concluded that there is no autocorrelation in the global regression model.

3.2.3 *Normality*

Normality testing in this research was conducted using two methods, namely the Shapiro-Wilk and Anderson-Darling tests. The Shapiro-Wilk test resulted in a p-value of 0.208, while the Anderson-Darling test yielded a p-value of 0.1563. A p-value greater than alpha (0.05) indicates the acceptance of the null hypothesis, suggesting that the residual data follows a normal distribution.

3.2.4 *Heteroscedasticity*

Heteroscedasticity testing is necessary for both global regression analysis and geographically weighted regression (GWR). In global regression analysis, data should be homogenous, but the opposite is true for geographically weighted regression. Based on the Breusch-Pagan test, a p-value of 0.017 was obtained, leading to the conclusion that the data's variance is heterogeneous and can be analyzed with GWR.

3.3 Global Regression Model

Table 4. Global Regression

Variables	Estimates	Std. Error	t-value	p-value (Sig)
Intercept	30.45	10.73	2.838	0.00674
X_1	6.795×10^{-5}	2.388×10^{-4}	0.285	0.77728
X_2	-0.2681	0.1260	-2.127	0.03880
X_3	5.709×10^{-7}	5.327×10^{-4}	0.107	0.91513
X_4	5.694×10^{-3}	2.726×10^{-2}	0.209	0.83546
X_5	-0.3478	0.2262	-1.538	0.13096
X_6	0.2268	7.853×10^{-2}	2.889	0.00588
X_7	-0.1442	6.506×10^{-2}	-2.217	0.03159
X_8	-0.1398	5.180×10^{-2}	-2.700	0.00968
X_9	-1.530×10^{-2}	2.855×10^{-2}	-0.536	0.59453

Based on Table 4, it can be shown that the variables that affect the percentage of poor people globally (all regencies/cities in West Kalimantan) are X_2, X_6, X_7, and X_8 because the probability values (p-value) are less than significance level (alpha = 0.05). The global regression model formed is stated as follows:

$$Y = 30.45 + 6.8 \times 10^{-5}X_1 - 0.27X_2 + 5.71 \times 10^{-7}X_3 + 5.69 \times 10^{-3}X_4 - 0.35X_5 + 0.23X_6 - 0.14X_7 - 0.14X_8 - 1.53 \times 10^{-2}X_9$$

This model means that the increase of X_2, X_5, X_7, X_8, and X_9 values can reduce the percentage of poor people.

3.4 GWR Assumption

Table 5. Spatial Assumption for GWR Model

Tests	p-value	Decisions
Moran's I	0.02414	Reject H0
Breusch Pagan	0.01709	Reject H0

Moran's I test indicated the existence of spatial autocorrelation so this model has spatial dependency. Meanwhile, the results of Breusch-Pagan also showed that there are significant differences in characteristics among observation points (the varians are heterogen). These results mean that we can continue the GWR calculation.

3.5 GWR Model

The next step is the selection of bandwidth that will be used in GWR modeling. The best model can be determined by examining the R^2 and AIC value between weighting functions. The weighting function used were fixed gaussian, fixed bisquare, fixed tricube, adaptive gaussian, adaptive bisquare, and adaptive tricube.

Table 6. Determination for the Best Model

Model	R^2	AIC
Gaussian	0.6672	203.64
Bisquare	0.7761	187.85
Tricube	0.8952	155.83
Adaptive Gaussian	0.6473	205.48
Adaptive Bisquare	0.5699	213.17
Adaptive Tricube	0.5378	215.91

The best model has the highest R^2 and the lowest AIC score. As shown in Table 6, fixed tricube model has the highest R^2 (0.8952) and the lowest AIC (155.83). So, the best GWR model uses a fixed tricube function. This R^2 value means that 89.52% of poor people percentage (Y) is affected by the independent variable in this research, and about 10.48% is affected by another variable.

To make sure that the GWR model has better results than global regression, ANOVA analysis is conducted. The results are shown in Table 7.

Table 7. Comparison between GWR and Global Regression

	SSE	df	F	p-value
Global Regression	145.99	46		
GWR	27.36	14.711	5.3352	0.000552

The p-value score (0.000552) is lower than alpha (0.05). Furthermore, the null hypothesis is declined and it can be concluded that the GWR model is better than global regression. GWR models and also the local R^2 for all 56 locations in Kalimantan on the nine independent variables are presented in Table 8.

Table 8. GWR Model for the 56 cities/regencies in Kalimantan

No	City / Regency	R^2	Model
1	Sambas	0.73	$Y = 5.31 + 3.98 \times 10^{-4}X_1 + 0.16X_2 - 8.72\times 10^{-6}X_3 - 0.14X_4 - 1.06X_5 + 0.28X_6 - 0.43X_7 - 0.12X_8 + 0.12X_9$

2	Bengkayang	0.74	Y = $6.15+3.88\times 10^{-4}X_1 + 0.14X_2 - 8.72\times 10^{-6}X_3 - 0.13X_4 - 1.05X_5 + 0.29X_6 - 0.43X_7 - 0.12X_8 + 0.12X_9$
3	Landak	0.75	Y = $5.60 + 3.51\times 10^{-4}X_1 + 0.14X_2 - 7.5\times 10^{-6}X_3 - 0.13X_4 - 0.97X_5 + 0.3X_6 - 0.44X_7 - 0.12X_8 + 0.13X_9$
4	Mempawah	0.74	Y = $2.46 + 3.37\times 10^{-4}X_1 + 0.19X_2 - 5.84\times 10^{-6}X_3 - 0.15X_4 - 0.89X_5 + 0.31X_6 - 0.46X_7 - 0.13X_8 + 0.13X_9$
5	Sanggau	0.75	Y = $9.65 + 3.75\times 10^{-4}X_1 + 0.09X_2 - 9.22\times 10^{-6}X_3 - 0.12X_4 - 1.01X_5 + 0.29X_6 - 0.43X_7 - 0.1X_8 + 0.12X_9$
6	Ketapang	0.80	Y = $6.66 + 3.45\times 10^{-4}X_1 + 0.09X_2 - 5.55\times 10^{-6}X_3 - 0.12X_4 - 0.63X_5 + 0.33X_6 - 0.46X_7 - 0.13X_8 + 0.14X_9$
7	Sintang	0.75	Y = $23.75 + 5.43\times 10^{-4}X_1 - 0.15X_2 - 2.26\times 10^{-5}X_3 - 0.05X_4 - 1.19X_5 + 0.28X_6 - 0.36X_7 - 0.7X_8 + 0.1X_9$
8	Kapuas Hulu	0.81	Y = $7.60 - 3.86\times 10^{-2}X_1 - 0.93X_2 - 9.53\times 10^{-5}X_3 + 0.13X_4 - 1.38X_5 + 0.06X_6 + 0.11X_7 + 0.01X_8 + 0.03X_9$
9	Sekadau	0.76	Y = $13.99 + 4.00\times 10^{-4}X_1 + 0.02X_2 - 1.17\times 10^{-5}X3 - 0.1X4 - 1.03X5 + 0.29X6 - 0.41X7 - 0.09X8 + 0.12X9$
10	Melawi	0.78	Y = $34.51 + 3.64\times 10^{-4}X_1 - 0.26X_2 - 1.34\times 10^{-5}X_3 - 0.07X_4 - 0.77X_5 + 0.29X_6 - 0.34X_7 - 0.06X_8 + 0.08X_9$
11	Kayong Utara	0.77	Y = $8.47 + 3.38\times 10^{-4}X_1 + 0.09X_2 - 5.77\times 10^{-6}X_3 - 0.12X_4 - 0.71X_5 + 0.3X_6 - 0.44X_7 - 0.12X_8 + 0.13X_9$
12	Kubu Raya	0.75	Y = $2.84 + 3.34\times 10^{-4}X_1 + 0.18X_2 - 5.77\times 10^{-6}X_3 - 0.14X_4 - 0.87X_5 + 0.31X_6 - 0.46X_7 - 0.13X_8 + 0.14X_9$
13	Pontianak	0.75	Y = $2.69 + 3.33\times 10^{-4}X_1 + 0.18X_2 - 5.69\times 10^{-6}X_3 - 0.14X_4 - 0.86X_5 + 0.31X_6 - 0.46X_7 - 0.13X_8 + 0.14X_9$
14	Singkawang	0.74	Y = $2.75 + 3.58\times 10^{-4}X_1 + 0.19X_2 - 6.7\times 10^{-6}X_3 - 0.14X_4 - 0.97X5 + 0.29X6 - 0.45X7 - 0.13X8 + 0.13X9$
15	Kotawaringin Barat	0.92	Y = $49.92 - 8.23\times 10^{-5}X_1 - 0.34X_2 + 1.4\times 10^{-5}X_3 - 0.03X_4 - 0.4X_5 - 0.04X_6 - 0.03X_7 - 0.09X_8 - 0.02X_9$
16	Kotawaringin Timur	0.98	Y = $24.05 + 5.91\times 10^{-4}X_1 - 0.01X_2 - 7.62\times 10^{-6}X_3 - 0.12X_4 - 0.33X_5 - 0.04X_6 - 0.08X_7 - 0.01X_8 + 0.01X_9$
17	Kapuas	0.88	Y = $24.66 + 1.89\times 10^{-4}X_1 - 0.12X_2 - 1.91\times 10^{-6}X_3 - 0.08X_4 - 0.2X_5 + 0.07X_6 - 0.2X_7 + 0.1X_8 + 0.06X_9$
18	Barito Selatan	0.93	Y = $-11.75 + 3.37\times 10^{-4}X_1 - 0.03X_2 - 6.05\times 10^{-6}X_3 + 0.1X_4 - 0.46X_5 + 0.26X_6 - 0.11X_7 - 0.17X_8 + 0.06X_9$
19	Barito Utara	0.97	Y = $48.87 - 6.06\times 10^{-4}X_1 - 0.89X_2 - 4.87\times 10^{-6}X_3 + 0.32X_4 - 0.44X_5 + 0.35X_6 + 0.03X_7 - 0.17X_8 - 0.05X_9$
20	Sukamara	0.90	Y = $43.24 - 2.17\times 10^{-4}X_1 - 0.27X_2 + 1.43\times 10^{-5}X_3 - 0.03X_4 - 0.395X_5 - 0.04X_6 - 0.03X_7 - 0.09X_8 - 0.2X_9$
21	Lamandau	0.86	Y = $38.64 + 2.27\times 10^{-6}X_1 - 0.25X_2 + 7.76\times 10^{-6}X_3 - 0.07X_4 - 0.3X_5 + 0.15X_6 - 0.23X_7 - 0.07X_8 + 0.04X_9$
22	Seruyan	0.95	Y = $71.40 + 2.57\times 10^{-5}X_1 - 0.54X_2 + 9.6\times 10^{-6}X_3 - 0.05X_4 - 0.46X_5 - 0.04X_6 - 0.01X_7 - 0.07X_8 - 0.04X_9$
23	Katingan	0.98	Y = $-20.29 + 2.06\times 10^{-4}X_1 + 0.51X_2 - 2.98\times 10^{-5}X_3 - 0.14X_4 - 0.05X_5 - 0.19X_6 - 0.04X_7 + 0.13X_8 + 0.02X_9$

24	Pulang Pisau	0.90	Y = $43.59 + 2.81 \times 10^{-4}X_1 - 0.24X_2 - 2.53 \times 10^{-5}X_3 - 0.1X_4 - 0.23X_5 + 0.02X_6 - 0.17X_7 + 0.15X_8 + 0.02X_9$
25	Gunung Mas	0.96	Y = $81.17 - 2.13 \times 10^{-2}X_1 - 0.67X_2 - 2.42 \times 10^{-5}X_3 - 0.05X_4 - 0.12X_5 - 0.13X_6 + 0.06X_7 + 0.08X_8 + 0.004X_9$
26	Barito Timur	0.92	Y = $-11.76 + 3.08 \times 10^{-4}X_1 + 0.09X_2 - 6.78 \times 10^{-6}X_3 + 0.03X_4 - 0.52X_5 + 0.22X_6 - 0.15X_7 - 0.13X_8 + 0.05X_9$
27	Murung Raya	0.98	Y = $85.61 - 1.15 \times 10^{-2}X_1 - 1.03X_2 - 6.45 \times 10^{-5}X_3 + 0.1X_4 - 0.42X_5 + 0.24X_6 + 0.07X_7 - 0.01X_8 - 0.06X_9$
28	Palangka Raya	0.91	Y = $26.85 + 2.88 \times 10^{-4}X_1 - 0.04X_2 - 2.57 \times 10^{-5}X_3 - 0.11X_4 - 0.17X_5 - 0.02X_6 - 0.13X_7 + 0.09X_8 + 0.01X_9$
29	Tanah Laut	0.86	Y = $16.78 + 1.26 \times 10^{-4}X_1 - 0.07X_2 - 1.58 \times 10^{-5}X_3 - 0.07X_4 - 0.23X_5 + 0.08X_6 - 0.19X_7 + 0.09X_8 + 0.08X_9$
30	Kotabaru	0.92	Y = $-5.85 + 4.62 \times 10^{-5}X_1 - 0.03X_2 - 8.92 \times 10^{-6}X_3 - 0.02X_4 - 0.27X_5 + 0.3X_6 - 0.21X_7 - 0.1X_8 + 0.13X_9$
31	Banjar	0.88	Y = $13.72 + 1.62 \times 10^{-4}X_1 - 0.07X_2 - 1.54 \times 10^{-5}X_3 - 0.05X_4 - 0.19X_5 + 0.11X_6 - 0.19X_7 + 0.06X_8 + 0.08X_9$
32	Barito Kuala	0.88	Y = $15.23 + 1.80 \times 10^{-4}X_1 - 0.07X_2 - 1.65 \times 10^{-5}X_3 - 0.06X_4 - 0.19X_5 + 0.1X_6 - 0.19X_7 + 0.07X_8 + 0.08X_9$
33	Tapin	0.88	Y = $7.65 + 1.28 \times 10^{-4}X_1 - 0.06X_2 - 1.23 \times 10^{-5}X_3 - 0.04X_4 - 0.19X_5 + 0.16X_6 - 0.2X_7 + 0.01X_8 + 0.1X_9$
34	Hulu Sungai Selatan	0.90	Y = $4.32 + 9.76 \times 10^{-5}X_1 - 0.07X_2 - 9.89 \times 10^{-6}X_3 - 0.03X_4 - 0.2X_5 + 0.2X_6 - 0.2X_7 - 0.02X_8 + 0.11X_9$
35	Hulu Sungai Tengah	0.91	Y = $-1.46 + 7.10 \times 10^{-5}X_1 - 0.05X_2 - 8.02 \times 10^{-6}X_3 - 0.02X_4 - 0.25X_5 + 0.26X_6 - 0.21X_7 - 0.07X_8 + 0.12X_9$
36	Hulu Sungai Utara	0.90	Y = $-2.45 + 1.45 \times 10^{-4}X_1 - 0.01X_2 - 9.53 \times 10^{-6}X_3 - 0.02X_4 - 0.3X_5 + 0.23X_6 - 0.2X_7 - 0.06X_8 + 0.11X_9$
37	Tabalong	0.92	Y = $-12.66 + 4.85 \times 10^{-5}X_1 + 0.01X_2 - 5.44 \times 10^{-6}X_3 + 0.001X_4 - 0.33X_5 + 0.3X_6 - 0.19X_7 - 0.11X_8 + 0.13X_9$
38	Tanah Bumbu	0.91	Y = $4.14 + 1.39 \times 10^{-5}X1 - 0.12X2 - 8.27 \times 10^{-6}X3 - 0.03X_4 - 0.18X_5 + 0.26X_6 - 0.22X_7 - 0.05X_8 + 0.14X_9$
39	Balangan	0.91	Y = $-10.45 - 3.24 \times 10^{-6}X_1 + 0.001X_2 - 6.46 \times 10^{-6}X_3 - 0.02X_4 - 0.29X_5 + 0.3X_6 - 0.22X_7 - 0.09X_8 + 0.14X_9$
40	Banjarmasin	0.87	Y = $19.13 + 1.56 \times 10^{-4}X_1 - 0.09X_2 - 1.69 \times 10^{-5}X_3 - 0.07X4 - 0.21X5 + 0.08X6 - 0.19X7 + 0.09X8 + 0.07X9$
41	Banjar Baru	0.87	Y = $15.29 + 1.34 \times 10^{-4}X_1 - 0.07X_2 - 1.52 \times 10^{-5}X_3 - 0.06X_4 - 0.21X_5 + 0.1X_6 - 0.19X_7 + 0.07X_8 + 0.08X_9$
42	Malinau	0.95	Y = $-55.74 - 6.60 \times 10^{-4}X_1 + 0.36X_2 - 2.09 \times 10^{-6}X_3 + 0.09X_4 - 1.13X_5 + 0.52X_6 - 0.15X_7 - 0.35X_8 + 0.03X_9$
43	Bulungan	0.94	Y = $-73.40 - 4.30 \times 10^{-4}X_1 + 0.65X_2 + 1.74 \times 10^{-7}X_3 + 0.08X_4 - 1.31X_5 + 0.4X_6 - 0.14X_7 - 0.42X_8 + 0.04X_9$

44	Tana Tidung	0.94	$Y = -81.18 - 4.61 \times 10^{-4}X_1 + 0.71X_2 - 6.03 \times 10^{-7}X_3 + 0.08X_4 - 1.32X_5 + 0.42X_6 - 0.15X_7 - 0.42X_8 + 0.05X_9$
45	Nunukan	0.94	$Y = -86.83 - 4.98 \times 10^{-4}X_1 + 0.71X_2 - 2.39 \times 10^{-6}X_3 + 0.08X_4 - 1.28X_5 + 0.51X_6 - 0.18X_7 - 0.42X_8 + 0.05X_9$
46	Tarakan	0.94	$Y = -76.32 - 3.32 \times 10^{-4}X_1 + 0.71X_2 + 8.02 \times 10^{-7}X_3 + 0.07X_4 - 1.35X_5 + 0.36X_6 - 0.13X_7 - 0.44X_8 + 0.04X_9$
47	Paser	0.97	$Y = 2.49 - 2.18 \times 10^{-3}X_1 - 0.27X_2 + 5.75 \times 10^{-6}X_3 + 0.19X_4 - 0.44X_5 + 0.24X_6 + 0.04X_7 - 0.14X_8 - 0.02X_9$
48	Kutai Barat	0.98	$Y = 55.52 - 2.09 \times 10^{-3}X_1 - 0.9X_2 + 6.85 \times 10^{-6}X_3 + 0.27X_4 - 0.51X_5 + 0.35X_6 + 0.03X_7 - 0.08X_8 - 0.08X_9$
49	Kutai Kartanegara	0.98	$Y = 45.02 - 2.16 \times 10^{-3}X_1 - 0.76X_2 + 8.00 \times 10^{-6}X_3 + 0.28X_4 - 0.42X_5 + 0.25X_6 + 0.1X_7 - 0.09X_8 - 0.11X_9$
50	Kutai Timur	0.97	$Y = -27.47 - 8.77 \times 10^{-5}X_1 + 0.37X_2 + 6.12 \times 10^{-6}X_3 + 0.07X_4 - 1.31X_5 + 0.09X_6 - 0.01X_7 - 0.39X_8 - 0.02X_9$
51	Berau	0.95	$Y = -51.61 - 2.59 \times 10^{-4}X_1 + 0.5X_2 + 2.8 \times 10^{-6}X_3 + 0.07X_4 - 1.31X_5 + 0.28X_6 - 0.09X_7 - 0.43X_8 + 0.02X_9$
52	Penajam Paser Utara	0.97	$Y = 14.59 - 1.73 \times 10^{-3}X_1 - 0.38X_2 + 7.99 \times 10^{-6}X_3 + 0.24X_4 - 0.48X_5 + 0.22X_6 + 0.08X_7 - 0.15X_8 - 0.08X_9$
53	Mahakam Ulu	0.97	$Y = 46.84 - 3.07 \times 10^{-3}X_1 - 0.98X_2 + 7.14 \times 10^{-6}X_3 + 0.37X_4 - 0.34X_5 + 0.38X_6 + 0.14X_7 - 0.01X_8 - 0.13X_9$
54	Balikpapan	0.98	$Y = 23.60 - 1.64 \times 10^{-3}X_1 - 0.5X_2 + 8.91 \times 10^{-6}X_3 + 0.27X_4 - 0.42X_5 + 0.21X_6 + 0.1X_7 - 0.15X_8 - 0.1X_9$
55	Samarinda	0.98	$Y = 42.94 - 2.07 \times 10^{-3}X_1 - 0.73X_2 + 8.26 \times 10^{-6}X_3 + 0.29X_4 - 0.4X_5 + 0.24X_6 + 0.1X_7 - 0.1X_8 - 0.11X_9$
56	Bontang	0.98	$Y = 42.68 - 2.06 \times 10^{-3}X_1 - 0.73X_2 + 8.28 \times 10^{-6}X_3 + 0.29X_4 - 0.4X_5 + 0.24X_6 + 0.1X_7 - 0.1X_8 - 0.11X_9$

The difference between GWR and global regression is clearly shown by Table 8, which gives 56 different models in each 56 locations. The R^2 scores are also different, with the range from 0.73 until 0.98.

After got the local model and R^2, partial significance tests were carried out to examine which parameters are significant. The t-statistic was used for the tests. If the t-statistic is higher than alpha (0.05), that variable is significant. The results were noted and grouped as in Table 9.

Table 9. Variables Affecting the Percentage of Poor People in each city/regency

City / Regency	Significant Variables
Kotawaringin Barat, Sukamara, Seruyan, Penajam Paser Utara	X_2
Katingan, Palangka Raya, Tanah Laut	X_3
Barito Selatan, Tabalong, Balangan, Paser	X_6

Kapuas, Lamandau, Pulang Pisau, Barito Timur, Banjar, Barito Kuala, Tapin, Hulu Sungai Selatan, Hulu Sungai Utara, Banjarmasin, Banjar Baru	X_7
Kutai Kartanegara, Balikpapan, Samarinda, Bontang	X_9
Gunung Mas	X_1, X_2
Murung Raya	X_2, X_3
Barito Utara	X_2, X_6
Kapuas Hulu	X_3, X_5
Melawi, Kotabaru, Hulu Sungai Tengah, Tanah Bumbu	X_6, X_7
Mahakam Ulu	X_1, X_4, X_6
Kutai Barat	X_2, X_6, X_9
Kotawaringin Timur, Kutai Timur, Berau	X_4, X_5, X_8
Malinau, Bulungan, Tana Tidung, Nunukan, Tarakan	X_4, X_5, X_6, X_8
Sambas, Bengkayang	X_6, X_7, X_8, X_9
Ketapang	X_4, X_6, X_7, X_9
Landak, Mempawah, Kayong Utara, Kubu Raya, Pontianak, Singkawang	X_4, X_6, X_7, X_8, X_9

4. DISCUSSIONS

The findings of this study demonstrate the significant spatial variability in poverty rates across different regencies and cities on the island of Kalimantan, which were effectively modeled using Geographically Weighted Regression (GWR) as opposed to Ordinary Least Squares (OLS) regression.
The superior performance of GWR in capturing spatial heterogeneity aligns with findings from prior studies, such as those by Astuti, Debataraja, and Sulistianingsih (2018) and Wahyudi, Fauzi, and Rizal (2023), which also noted the enhanced explanatory power of GWR in spatial analyses. In particular, this study's results corroborate the argument that local variations in factors influencing poverty are substantial and must be accounted for to achieve more accurate models. However, unlike previous studies which primarily focused on different regions of Indonesia, this research highlights the unique socio-economic dynamics within Kalimantan, thus contributing new insights to the existing body of knowledge.

Research Implications
The implications of this study are multifaceted:

1. The demonstrated efficacy of GWR supports the need for spatially adaptive methods in socio-economic research. This study strengthens the theoretical foundation that spatial heterogeneity significantly affects socio-economic phenomena and that GWR is a valuable tool for revealing such complexities.
2. For policymakers and regional planners, these findings highlight the necessity of localized interventions. The identification of specific factors influencing poverty in different areas allows

for more targeted and effective policy measures. For instance, regions where economic variables (such as employment rates) are significant predictors of poverty can benefit from job creation programs, while areas influenced by educational factors might prioritize educational improvements.

3. Future research could build on these findings by incorporating additional variables or exploring other regions. The relatively high R^2 value of 89% suggests that while the model is robust, there is still room for improvement. Further studies could enhance the model's precision by including more granular data or employing alternative spatial analysis techniques like Mixed Geographically Weighted Regression (MGWR).

This study not only provides valuable insights for the island of Kalimantan but also sets a precedent for similar research in other regions. By demonstrating the effectiveness of GWR in modeling spatial data, this research encourages its broader application in various socio-economic studies. The ability to understand and address local disparities is crucial for achieving equitable development and informed decision-making. Moreover, the findings advocate for a paradigm shift in policy formulation, emphasizing the need for spatially nuanced approaches rather than one-size-fits-all solutions. Such a shift could lead to more effective poverty alleviation strategies and contribute to the overall goal of sustainable development.

Therefore, this research underscores the critical role of spatial analysis in understanding and addressing socio-economic issues. The application of GWR not only provides a more accurate depiction of the factors influencing poverty but also offers actionable insights for policymakers and researchers. The implications drawn from this study highlight the importance of localized interventions and the potential for future research to further refine our understanding of spatial socio-economic dynamics.

5. CONCLUSION

This study demonstrates that Geographically Weighted Regression (GWR) outperforms Ordinary Least Squares (OLS) regression in modeling spatial data. By using the fixed tricube weighting function, GWR can generate regression models and factors influencing the poverty rate that vary for each regency or city on the island of Kalimantan. The overall R^2 score obtained by the GWR model is 89%, while the R^2 score for each city and regency ranged from 0.73 to 0.98. It means that the indicators conducted in this research were good enough to model the level of poverty. From 56 cities and regencies in Kalimantan, 17 regional groups were formed with similar indicators that influence the regional poverty level. These results can provide additional information for the government regarding factors that must be addressed in order to reduce poverty levels in these regional groups. The next research can be conducted by adding more various independent variable to get higher score of coefficient determination and more suitable model.

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