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Research Paper

Georaphically Weighted Ridge Regression Modelling on 2023 Poverty Indicators Data in the Provinces of West Kalimantan and Central Kalimantan

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Geographically Weighted Ridge Regression (GWRR), Spatial Heterogeneity, Multicollinearity

Abstract
Regression analysis is a method to explain the relations between independent variables and a dependent variable. Linear regression analysis relies on certain assumptions, one of the assumption is homogeneity. However, there is a situation when the variance at each observation differs or called spatial heterogeneity.This issue can be solved using Geographically Weighted Regression (GWR), a statistical method that can be fixed spatial heterogeneity by adding a local weighted matrix, the result in GWR model is a local model for each observation point. However, GWR has a limitation, it cannot handle multicollinearity. Ridge regression is a method used to solved multicollinearity by adding a bias constant (λ). A GWR model that contains multicollinearity and fixed using ridge regression is known as Geographically Weighted Ridge Regression (GWRR).

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1. INTRODUCTION

Linear regression analysis is a method to explain the relationship between independent variables and a dependent variable. A good linear regression model has certain assumptions. However, there is a situation where the characteristics at each observation location differ, called spatial heterogeneity.A statistical method for regression analysis on data with spatial heterogeneity is Geographically Weighted Regression (GWR). The GWR model analyzes spatial variation in the data by forming a regression model that considers local aspects at each observation location. This method is effective in estimating parameters for data with spatial heterogeneity conditions [1].

One of the problems in the GWR model is the presence of correlation among several independent variables. Correlation among independent variables, or multicollinearity, can cause instability in parameter estimation. A method to resolve multicollinearity is ridge regression. A GWR case that involves multicollinearity using ridge regression is known as Geographically Weighted Ridge Regression (GWRR).

Poverty is a condition where an individual or a community faces economic hardship. According to Statistics Indonesia (BPS), poverty is affected by several indicators, like the number of poor people, the Poverty Depth Index, and the Poverty Severity Index. The Poverty Depth Index and the Poverty Severity Index calculated from other poverty indicators the number of poor people, which indicates multicollinearity among the poverty indicators. According to BPS in 2023, West Kalimantan and Central Kalimantan are provinces with high poverty rates in Kalimantan. Geographically, West Kalimantan and Central Kalimantan share a border. However, they have different geographical characteristics, indicating spatial heterogeneity.

Research on GWR by [2, 3], shows that the GWR model can detect variations in characteristics at each location and handles them properly. GWR provides more accurate information compared to the ordinary multiple linear regression model [4]. Through the GWR model, differences in location characteristics will assign different weights to each location. This will result in different significant variables at each location [5]. With such performance, GWR is highly suitable for use in various types of data, such as health and natural phenomena and disasters. In the health sector, GWR has been used in data on pneumonia cases in children under five [6]. GWR research has also been conducted by A using flood disaster data in South Kalimantan [7].

Ridge regression is a method used to address multicollinearity. Research on ridge regression by [8, 9], results that ridge regression effectively overcomes multicollinearity. There is an improvement in ridge regression, such as the jackknife ridge regression discussed in the journal by Arrasyid [10]. Similarly, this study will explore advancements in ridge regression applied to data with spatial heterogeneity, specifically through Geographically Weighted Ridge Regression (GWRR).

In Geographically Weighted Regression (GWR) modeling, there are various conditions that can result in the GWR model becoming unstable. These conditions have encouraged the development of extended GWR models. For example, when the data show variance greater than the mean (overdispersion) that used the GWNBR model, when only part of the data shows varying influence, the MGWR model is applied, and GWNR for modeling without assuming a specific form of relationship between variables [11, 12, 13, 14]. This study will apply to spatial data with multicollinearity by adding ridge regression into the GWR model.

Geographically Weighted Ridge Regression has been applied in previous studies, such as to modelling a locally generated revenue in Central Java in 2016, to fixed multicollinearity in the Human Development Index (HDI) of East Java in 2017, applied in 2017 stunting data of East Nusa Tenggara in 2020, to modelling the open unemployment rate in West Kalimantan in 2023, and modelling in stunting measurement data of Indonesia in 2023. These studies have shown that Geographically Weighted Ridge Regression is capable of addressing multicollinearity issues in spatial data [15, 16, 17].

Based on this background, this study will apply the Geographically Weighted Ridge Regression (GWRR) model to the 2023 poverty indicator data for the provinces of West Kalimantan and Central Kalimantan.

2. METHODS

This study aims to model Geographically Weighted Ridge Regression (GWRR) using poverty indicator data for West Kalimantan and Central Kalimantan Provinces, and to investigate which indicators influence each Regency/City in those provinces in the year 2023. This research uses RStudio software. The steps carried out in this study are as follows:

2.1 Data Exploration

This step involves descriptive analysis and data visualization of the poverty indicators data in 2023 in the provinces of West Kalimantan and Central Kalimantan. The poverty indicators used in this study include the number of poor people (Y), the Poverty Depth Index(X_1), and the Poverty Severity Index (X_2).

2.2 Spatial Heterogeneity Test

Spatial heterogeneity in a regression model refers to a condition where there are differences in characteristics between observation points due to geographic or socio-cultural factors.

2.3 Multicollinearity Test

Multicollinearity is a condition when two or more independent variables are linearly related to each other [18]. The indicator that can be used to detect multicollinearity is the Variance Inflation Factor (VIF). If VIF values more than 10 that indicates the presence of multicollinearity among the independent variables.

2.4 Calculating Euclidean Distance

Euclidean distance is calculated based on the geographical coordinates (longitude and latitude).

2.5 Bandwidth (h)

Bandwidth (h) is a radius around the center point of a location and is used to determine the weighting at each location. Observations closer to location i have a greater influence on estimating the parameters at location i. One of method to determine the optimal bandwidth is Cross Validation (CV).

2.6 Calculating Weighted Matrix

Calculating Weighted Matrix for the Geographically Weighted Regression Model. The weighted function in GWR provides local parameter estimates that are affected by neighbor location point [19].

2.7 Parameters Estimated of the GWR Model

The local parameter estimates for the GWR model are obtained using the following formula:

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

Explanation:

f = dependent variable
Z = full-rank matrix of independent variables
$\hat{\beta}(u_i, v_i)$ = local coefficient estimates at location i
$W(u_i, v_i)$ = local weighted matrix for location i

2.8 Geographically Weighted Ridge Regression (GWRR) Modelling

GWRR is a method designed to fixed multicollinearity in spatial data [20]. GWRR is an extension of ridge regression that incorporates local weights. Ridge regression is a method used to fix high correlation among independent variables (multicollinearity) in a regression model, which can lead to unstable parameter estimates. The optimal bias constant can be determined using Generalized Cross Validation (GCV). After the optimal lambda is obtained, the next step is to estimate the parameters of the GWRR model. The formula for local parameter estimation in GWRR is:

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$$y_i = \beta_0^R(u_i, v_i) + \sum_k \beta_k^R(u_i, v_i)x_{ik} + \varepsilon_i \quad (2)$$

Explanation:

$\hat{\beta}(u_i, v_i)$	= local ridge coefficient estimates at location i
f	= dependent variable
Z	= full-rank matrix of independent variables
$W(u_i, v_i)$	= local weighted matrix for location i
λ	= ridge bias parameter
I	= Identity matrix

2.9 Testing Model Parameters

Parameter testing in GWR is conducted partially for each observation point to determine the significance of parameters at each location. The partial test or t-test is a procedure used to accept or reject a hypothesis based on the sample results. The t-test formula is:

$$t_{\text{hit}}(u_i, v_i) = \frac{\hat{\beta}_k(u_i, v_i)}{S\{\hat{\beta}_k(u_i, v_i)\}} \quad (3)$$

Explanation:

$\hat{\beta}_k(u_i, v_i)$	= local coefficient for variable k at location i
$S\{\hat{\beta}_k(u_i, v_i)\}$	= standard error of the local coefficient

2.10 Model Goodness-of-Fit Test using AIC

The goodness-of-fit test evaluates how well the model explains the data. The Akaike Information Criterion (AIC) is one such good test for Goodness-of fit. The best regression model is the one with the lowest AIC value.

3. RESULTS AND DISCUSSION

In this study, the Geographically Weighted Ridge Regression (GWRR) model will be applied to fix multicollinearity issues in the 2023 poverty indicator data for West Kalimantan and Central Kalimantan provinces. Before starting GWRR modelling, the Geographically Weighted Regression (GWR) model will be constructed, and a bias constant (λ) will be added to build the GWRR model. After both models are produced, a comparison between the model.

3.1 Exploration of Poverty Indicator Data

Before starting the data processing, there will be a data exploration process to provide an overview of the dataset. Descriptive analysis offers a general overview of the condition of the poverty indicator data. The descriptive analysis of poverty indicator data for West Kalimantan and East Kalimantan is presented as follows:

Based on Table 1, the highest number of poor people in West Kalimantan and Central Kalimantan is 49.95 thousand people, and the lowest is 2.63 thousand people. Next, to understand the poverty conditions in each region, mapping each poverty indicator in West Kalimantan and Central Kalimantan will be conducted.

Table 1. Descriptive Analysis of Poverty Indicators Data

Variable	Mean	Median	Max	Min
Y	17.6979	13.795	49.95	2.63
X1	0.8450	0.705	2.47	0.27
X2	0.2136	0.155	0.83	0.04

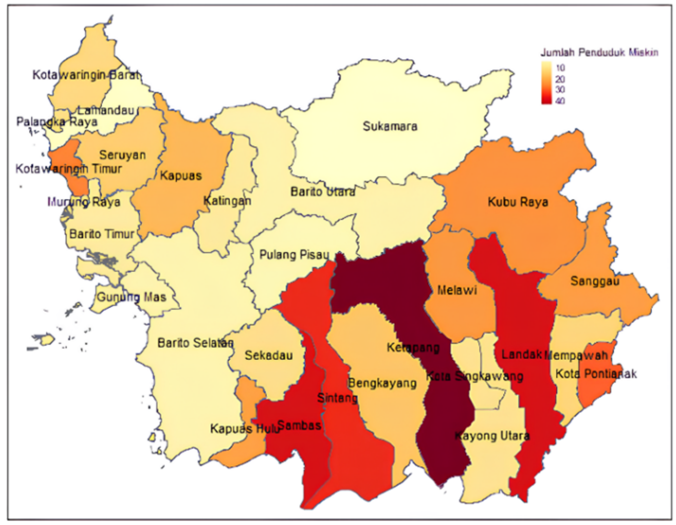

Figure 1. Map of the Number of Poor People in Districts/Cities of West Kalimantan and Central Kalimantan

Based on Figure 1, the number of poor people shows data variation across regions. Although West Kalimantan and Central Kalimantan share a border, poverty levels in Central Kalimantan are higher than in West Kalimantan. This indicates the presence of spatial heterogeneity in the data.

Based on Figure 2, the Poverty Depth Index also shows variation across regions, indicating the presence of spatial heterogeneity in the data.

Based on Figure 3, the Poverty Severity Index shows regional variation across all areas. In addition, the data distribution of the Poverty Depth Index and Poverty Severity Index appears nearly identical in each region, indicating the presence of multicollinearity in the data.

3.2 Spatial Heterogeneity Test

Based on the previous data exploration, there is an indication that the data contains spatial heterogeneity. Therefore, a Breusch-Pagan test will be conducted to confirm the presence of data variability that leads to spatial heterogeneity. Spatial heterogeneity is checked using the Breusch-Pagan test with the following formula:

$$BP = \left(\frac{1}{2}\right) f^T Z(Z^T Z)^{-1} Z^T f \quad (4)$$

Explanation:

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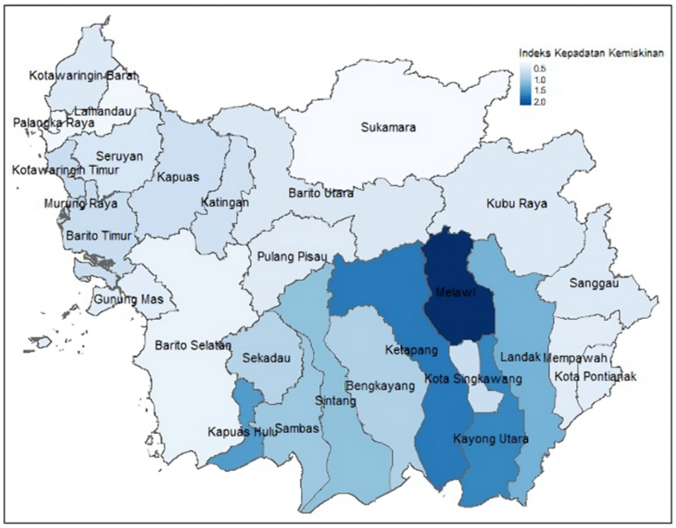

Figure 2. Map of Poverty Depth Index in Districts/Cities of West Kalimantan and Central Kalimantan

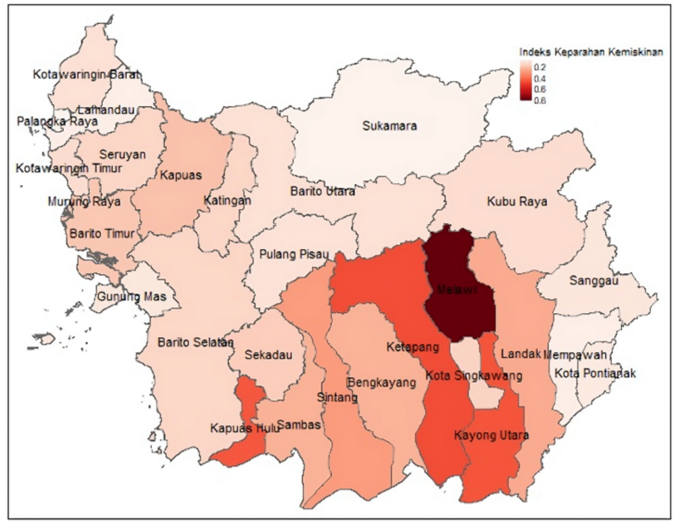

Figure 3. Map of Poverty Severity Index in Districts/Cities of West Kalimantan and Central Kalimantan Provinces

f = an $n \times 1$ vector, with $f = \left(\frac{\varepsilon_i^2}{\sigma^2} - 1\right)$ and $\varepsilon_i = y_i - \hat{y}_i$

Z = full-rank matrix of independent variables and intercept $(n \times (p+1))$

The results of the BP test are as follows:

Table 2. Breusch-Pagan Test Result

Test	Statistic test	P-value
Breusch-Pagan	7.4862	0.02368

Based on the Breusch-Pagan test result, p-value = 0.02368< 0.05, so reject H_o. This indicates the presence of spatial heterogeneity.

3.3 Multicollinearity Test

From the data exploration, there is an indication that the Poverty Depth Index and the Poverty Severity Index are correlated, or multicollinearity is present. Multicollinearity is checked using the Variance Inflation Factor (VIF), calculated as:

$$VIF_k = \frac{1}{1 - R_k^2} \tag{5}$$

Explanation:

k = $1, 2, \ldots, p$, with p being the number of independent variables

R_k^2 = coefficient determination of the other independent variables.

The results of the VIF are as follows:

Table 3. Variance Inflation factor Values

Variable	VIF VALUE
x_1	18.098
x_2	18.098

Based on Table 3, variables x_1 and x_2 have VIF values of 18.098 > 10. Therefore, we reject H_o, meaning multicollinearity is present between variables x_1 and x_2.

3.4 Geographically Weighted Regression Modelling on Poverty Indicator Data in West Kalimantan and Central Kalimantan

The Geographically Weighted Regression (GWR) modelling begins with calculating the Euclidean distance and determining the bandwidth value to construct the weight matrix, which will be used in the parameter estimation stage of the GWR model. The euclidean distance formula is:

$$d_{ij} = \sqrt{(u_i - v_i)^2 + (u_j - v_j)^2}, \tag{6}$$

with (u_i, v_i) is the coordinates of the i location (longitude, latitude). Based on formula, by using the coordinates u_i (longitude) and v_i (latitude), the Euclidean distance is shown in Table 4.

Table 4 shows the distances of 5 location points from Kotawaringin Barat and Kotawaringin Timur.

The bandwidth value is obtained based on CV score, defined as:

$$CV(h) = \sum_{i=1}^{n} \left[y_i - \hat{y}_{\neq i}(h)\right]^2 \tag{7}$$

$\hat{y}_{\neq i}$ is the predicted value of y_i with excluding the observation at location i. The optimal bandwidth is the value of h that minimizes the CV score through iteration [1]. The optimal bandwidth result using the CV method is shown in Table 5.

Based on Table 5, the optimal bandwidth value is 7.166237 with a minimum CV value of 3106.798. From the Euclidean

Table 4. Euclidean Distance

Location (u_i,v_i)	Kotawaringin Barat	Kotawaringin Timur
Kotawaringin Barat	0.00000	0.00082
Kotawaringin Timur	0.00082	0.00000
Kapuas	6.96461	6.96386
Barito Selatan	9.04471	9.04427
Barito Utara	9.75603	9.75555

Table 5. Bandwidth Value Based on Cross Validation

Fixed bandwidth	Cross Validation score
3.795518	3216.544
7.246987	3206.8
7.377644	3206.809
7.166237	3206.798
7.116331	3206.798

Table 6. Local Weight Matrix

Location (u_i,v_i)	Kotawaringin Barat	Kotawaringin Timur
Kotawaringin Barat	1.0000000	0.9998862
Kotawaringin Timur	0.9998862	1.0000000
Kapuas	0.3783771	0.3784164
Barito Selatan	0.2830510	0.2830683
Barito Utara	0.2563047	0.2563220

Table 7. GWR Parameter Estimates

Location	β_0	β_1	β_2
Kotawaringin Barat	0.36852	50.08077	- 115.370
Kotawaringin Timur	0.36878	50.08078	-115.371
Kapuas	2.87443	43.51693	-99.432
Barito Selatan	1.35737	38.82067	-81.673
Barito Utara	1.45392	37.92861	-78.991

Table 8. Significant Paramater Group in GWR

Parameter	Location
β_1	Kapuas, Barito Selatan, Barito Utara, Seruyan, Katingan, Pulau Pisau, Barito Timur, Murung Raya, Palangka Raya, Sanggau, Sintang, Kapuas Hulu, Sekadau, dan Melawi.
β_1 and β_2	Kotawaringin Barat, Kota Waringin Timur, Sukamara, Lamandau, Gunung Mas, Sambas, Bengkayang, Landak, Mempawah, Ketapang, Kayong Utara, Kubu Raya, Pontianak, dan Singkawang.

distance and the bandwidth value, a local weighted matrix will be constructed. This study uses the exponential kernel weighted function, defined as:

$$w_j(u_i, v_i) = \exp\left[-\frac{d_{ij}}{h}\right] \tag{8}$$

The weighted matrix for each location is shown in Table 6.

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Table 6 shows the weight matrix between 5 location points and Kotawaringin Barat and Kotawaringin Timur.

3.5 Parameters Estimation of GWR Model

After obtaining the local weight matrix in Table 6, the next step is to estimate the parameters of the Geographically Weighted Regression (GWR) model using the Weighted Least Squares (WLS) estimator. The results of the local parameter estimation for each observation point are presented in Table 7.

Table 7 shows the estimation of parameters for 5 location points.Once the parameter estimates are obtained, we will check the significant parameters using the t-test. The significant variables of each location are as follows:

Based on Table 8, the Poverty Depth Index (X_1)is significant for all locations and the Poverty Severity Index (X_2) is significant for 14 locations.

3.6 Geographically Weighted Ridge Regression Modelling on Poverty Indicator Data in West Kalimantan and Central Kalimantan

The application of ridge regression in the Geographically Weighted Regression (GWR) model aims to fix multicollinearity by adding a bias constant (λ) through the Generalized Cross Validation (GCV) method, defined as:

$$GCV = \frac{\sum_{i=1}^{n} e_{i,\lambda}^2}{\{n - [1 + \text{tr}(H_\lambda)]\}^2} \tag{9}$$

Explanation:

$e_{i,\lambda}^2$ = sum square of i for a given λ
H_λ = hat matrix

The optimal (λ) value is presented in Table 9.

Table 9. Ridge Regression Bias Constant

Bias constant (λ)	GCV Score
0.0	3.654.284
0.1	3.633.345
0.2	3.632.558
0.3	3.642.114
0.4	3.656.890

Based on Table 9, the best (λ) value is 0.2, with a minimum GCV value of 3,632.588. The selected (λ) value will then be applied to the local parameter estimates obtained from the GWR modelling. The results of the local parameter estimation for the Geographically Weighted Ridge Regression (GWRR) model are shown in Table 10.

Table 10 shows the estimation of parameters for 5 location points. After obtaining the parameter estimates of the GWRR model, we will check the significant parameters using the t-test. The significant variables of each location shown in Table 11.

Based on Table 11, the Poverty Depth Index (X_1)is significant for all locations and the Poverty Severity Index (X_2) is significant in 13 locations. After obtaining the significant parameters at each location, the GWRR model is presented in Table 12.

Table 12 shows a GWRR model for 5 locations. Compared to the GWR model, the parameters in the GWRR model have decreased, indicating a reduction in the residual sum of squares, which means that the GWRR model provides a better fit. Based on the GWRR model in Table 12, the prediction results are obtained as follows:

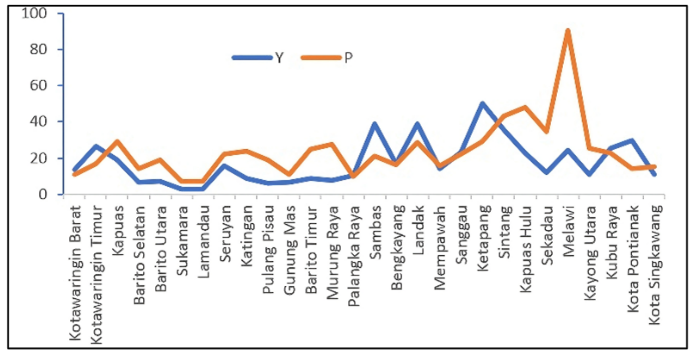

Figure 4. GWRR Model Prediction

Based on Figure 4, it can be seen that the predictions from the Geographically Weighted Ridge Regression model perform well, as the predicted results are able to follow the general pattern of the actual data.

3.7 Goodness-of-Fit Model

After obtaining the GWR and GWRR models, a goodness-of-fit test will be conducted using the Akaike Information Criterion (AIC). A lower AIC value indicates a better-fitting model. AIC is calculated as:

$$AIC = -2\log(\hat{L}) + 2k \tag{10}$$

Explanation:

k = number of parameters, including the intercept
$\hat{L}$ = log-likelihood

The following is a comparison between the AIC values of the GWR and GWRR models.

Based on Table 13, it is shown that the GWRR model with an AIC score of 131.303 is better than the GWR model with an AIC score of 206.105. This indicates that the GWRR modelling can address multicollinearity issues through the addition of a bias constant (λ), which leads to a reduction in the error variance present in the GWR model.

4. CONCLUSIONS

Based on the analysis result, the Geographically Weighted Ridge Regression (GWRR) model is capable of fixing both spatial heterogeneity and multicollinearity in the 2023 poverty indicator

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Table 10. GWRR Parameter Estimates

Location	β_0	β_1	β_2
Kotawaringin Barat	0.5229	40.6318	-93.02
Kotawaringin Timur	0.5230	40.6321	-93.02
Kapuas	2.9971	35.7525	-82.44
Barito Selatan	1.1315	31.7365	-66.15
Barito Utara	1.2148	30.8030	-63.32

Table 11. Significant Parameter Groups in GWRR

Parameter	Location
β_1	Kapuas, Barito Selatan, Barito Utara, Seruyan, Katingan, Pulau Pisau, Barito Timur, Murung Raya, Palangka Raya, Sanggau, Sintang, Kapuas Hulu, Sekadau, Melawi, Kayong Utara, dan Kubu Raya.
β_1 and β_2	Kotawaringin Barat, Kota Waringin Timur, Sukamara, Lamandau, Gunung Mas, Sambas, Bengkayang, Landak, Mempawah, Ketapang, Kubu Raya, Pontianak, dan Singkawang.

Table 12. GWRR Model

Location	GWRR model
Kotawaringin Barat	$y=0.522+ 40.63\ x_1 - 93.02\ x_2$
Kotawaringin Timur	$y= 0.523+40.63\ x_1- 93.02\ x_2$
Kapuas	$y= 2.997+35.75\ x_1$
Barito Selatan	$y= 1.131+31.74\ x_1$
Barito Utara	$y= 1.214+30.80\ x_1$

Table 13. AIC Scores

Model	AIC Score
Geographically Weighted Regression	206.105
Geographically Weighted Ridge Regression	131.303

data for West Kalimantan and Central Kalimantan. Therefore, it can be concluded that applying ridge regression within the GWR model is effective in handling multicollinearity in spatial data. In the model, the Poverty Depth Index variable (x_1) has a significant effect in all cities/districts and the Poverty Severity Index variable (x_2) shows a significant effect in 13 cities/districts.

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