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Analysis of Geographically Weighted Logistic Regression Models with A Bisquare Weighting Matrix on Poverty Status in West Java

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Abstract

This research addresses the first Sustainable Development Goal and aims to analyze poverty status in West Java Province, which has the second highest number of poor people in Indonesia. The study employs Geographically Weighted Logistic Regression (GWLR) and compares it with global logistic regression. Influential variables include GDP, unemployment, population density, access to safe water, and roof type (bamboo/wood). Results show that 55.6% of regions are classified as poor. The GWLR model using a Fixed Bisquare kernel achieves a higher accuracy of 81.4% (90% CI: 0.644, 0.919), whereas the GLR model achieves an accuracy of only 62.9% (90% CI: 0.453, 0.779). These spatial variations suggest that poverty reduction requires a region-specific approach. Consequently, policies should be formulated considering the priorities and characteristics of each region in West Java Province.

Keywords: Bisquare Weighting Matrix, Geographically Weighted Logistic Regression, Poverty, Spatial Analysis, West Java.

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1. Introduction

Poverty remains a serious issue in Indonesia, particularly in the West Java Province, which has a large population and diverse regions. According to data from Statistics Indonesia (BPS) [1], the number of poor residents in this province reached 3.8 million people (7.62% of the population), the second highest after East Java. Its distribution is uneven and exhibits a spatial pattern, where certain areas tend to have higher poverty levels. Government initiatives, such as the Family Hope Program (PKH), have been implemented [2]; however, the acceleration of rural development has yet to be fully optimized [3]. Therefore, a spatial approach is necessary to capture the uneven distribution of poverty, aligning with the first goal of the Sustainable Development Goals (SDGs): "No Poverty."

One such method, Geographically Weighted Logistic Regression (GWLR), is particularly relevant in this context as it incorporates geographic location factors into modeling. GWLR allows parameters to vary between locations, which makes it suitable for data with spatial heterogeneity [4]. This method can capture variations in the relationships between predictor and response variables between locations, which cannot be explained by global logistic regression [5].

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The spatial weighting function plays a crucial role in GWLR, with adaptive Gaussian kernels and bisquare kernels both proven effective in capturing spatial structures [6].

A study by [7] using multiple linear regression found that population density and Gross Regional Domestic Product (GRDP) per capita significantly influence poverty levels, whereas the open unemployment rate does not. Meanwhile, [8] showed that access to safe water has a significant effect on poverty. However, no study has specifically examined the effect of roof type (bamboo/wood), even though it may reflect household welfare.

This study categorizes the poverty level into two groups — poor and non-poor — based on a predefined threshold, following the approach adopted by previous research such as [9], which also employed the Geographically Weighted Logistic Regression (GWLR) model to capture spatial variations in poverty determinants. In the context of West Java, a spatial GWLR approach was previously applied by [10] to analyze poverty in 2022 using an adaptive Gaussian kernel weighting function. The study found that the GRDP per capita and population density are significant variables. Although the results were promising, further improvements are possible, particularly in the selection of variables and weighting functions [11].

GWLR is well suited for this study as its coefficients can be interpreted as odds ratios, which makes the results more relevant for policy analysis, and it is more robust to the nonnormal and heterogeneous distribution of binary poverty data since it employs a binomial framework instead of assuming normality. This research offers novelty in three aspects: the use of 2023 poverty data for West Java, the application of a bisquare kernel weighting function, and the inclusion of more relevant predictor variables, such as the percentage of households with bamboo/wood roofing. The results are expected to be more accurate and applicable to area-based poverty alleviation policies. Considering previous studies, this research will utilize variables such as GRDP per capita, population density, open unemployment rate, access to safe water, and the percentage of households with bamboo/wood roofing. The selection of variables in this study is based on previous research and represents a form of novelty in this analysis by including the roof type (bamboo/wood) variable, which may reflect the level of household welfare and influence the poverty rate in West Java Province. A significance level of 10% was adopted in this study to increase the sensitivity in detecting potential spatial heterogeneity, as spatial data often exhibit complex local correlations that may reduce statistical power under stricter thresholds. This criterion allows early identification of spatial dependence before proceeding with GWLR estimation.

By integrating the spatial GWLR approach with representative variables, this study aims to construct a predictive poverty model that reflects geographic patterns, providing a stronger foundation for more effective poverty alleviation strategies and contributing to the achievement of the SDGs in line 1.

2. Methods

2.1. Data Source

This study used secondary data previously accessible on the West Java Province's official website, which included information on nine cities and eighteen regencies. The variables to be further examined in Table 1 are described below.

2.2. Research Stages

2.2.1. Thematic Mapping and Descriptive Statistical Analysis

The study began with descriptive analysis to profile the data, followed by thematic mapping to visualize poverty distribution across West Java regions.

Table 1: Variables, Scales, and Units

Variable	Scale	Unit / Description
Poverty Percentage (Y)	Binary	0: Regency/City with poverty rate below provincial level (Not Poor) 1: Regency/City with poverty rate above provincial level (Poor)
GRDP Per Capita (X_1)	Ratio	Thousand Rupiah
Open Unemployment Rate (X_2)	Ratio	Percent (%)
Population Density (X_3)	Ratio	People per km^2
Percentage of households with access to safe water (X_4)	Ratio	Percent (%)
Percentage of households with bamboo and wooden roofs (X_5)	Ratio	Percent (%)

2.2.2. Global Logistic Regression Modeling

Logistic regression is a statistical method used to analyze the relationship between independent variables and a dependent variable with two categories (dichotomous) or more (polytomous). The global logistic regression model is used to assess the effect of predictor variables on poverty status overall, without considering spatial effects. Parameter estimation is performed using Maximum Likelihood Estimation (MLE), with the general equation:

$$\pi(x) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)} \tag{1}$$

The model is transformed into the logit form through a logarithmic transformation [12]:

$$g(x) = \ln \frac{\pi(x)}{1 - \pi(x)} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \tag{2}$$

Parameters were estimated using Maximum Likelihood Estimation (MLE) by maximizing the log-likelihood function[13]:

$$l(\beta) = \sum_{i=1}^{N} \left[y_i \ln \pi(x_i) + (1 - y_i) \ln(1 - \pi(x_i)) \right] \tag{3}$$

The first derivative with respect to β_j is

$$\frac{\partial l(\beta)}{\partial \beta_j} = \sum_{i=1}^{N} X_{ij}(y_i - \pi(x_i)) = 0, \quad j = 0, 1, 2, ..., p \tag{4}$$

As this equation is non-linear, Newton-Raphson iteration was used to estimate $\hat{\beta}$ [6].

2.2.3. Spatial Assumption Testing

In spatial analysis, testing spatial assumptions is important to detect the effects of spatial dependence and inhomogeneity. Spatial heterogeneity is tested using Breusch-Pagan to check whether the residual variance is constant or varies across locations [14].

$$\begin{aligned} H_0 &: \quad \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2 \\ H_1 &: \quad \text{at least one } \sigma_i^2 \neq \sigma^2 \end{aligned}$$

The test statistic used in the Breusch-Pagan test is as follows [15]:

$$BP = \frac{1}{2} f^T Z (Z^T Z)^{-1} Z^T f \tag{5}$$

where Z is the matrix of explanatory variables of size $n \times (k+1)$. The null hypothesis H_0 is rejected if the test statistic $BP > \chi^2_{(p)}$, indicating the presence of spatial heterogeneity in the data.

Spatial dependency was tested using Moran's I:

$$\begin{aligned} H_0 :&\quad \text{no spatial dependency} \\ H_1 :&\quad \text{presence of spatial dependency} \end{aligned}$$

The test statistic used in Moran's I is as follows [16]:

$$Z = \frac{I - E(I)}{\sqrt{\text{Var}(I)}} \tag{6}$$

with

$$E(I) = -\frac{1}{n-1} \tag{7}$$

$$Var(I) = \frac{n^2 S_1 - n S_2 + 3S_0^2}{(n^2-1)S_0^2} - [E(I)]^2 \tag{8}$$

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{9}$$

$$S_1 = \frac{1}{2}\sum_{i\neq j}^{n}(w_{ij} + w_{ji})^2 \tag{10}$$

$$S_2 = \frac{1}{2}\sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2 \tag{11}$$

The null hypothesis H_0 is rejected if $|Z| = Z_{\alpha/2}$, indicating the presence of spatial dependency in the data.

2.2.4. Geographically Weighted Logistic Regression (GWLR)

Geographically Weighted Logistic Regression (GWLR) is a spatial extension of the binary logistic regression model that incorporates geographic location through a spatial weighting function w_{ij}. By estimating regression parameters locally at each coordinate (u_i, v_i), GWLR effectively captures spatial heterogeneity that conventional logistic regression, which assumes global stationarity, is unable to reveal. The general GWLR model is formulated as [17]:

$$\pi(X_j) = \frac{\exp\left(\sum_{k=0}^{p} \beta_k(u_i, v_i) x_{jk}\right)}{1 + \exp\left(\sum_{k=0}^{p} \beta_k(u_i, v_i) x_{jk}\right)} \tag{12}$$

$$X_j = \ln \frac{\pi(X_j)}{1-\pi(X_j)} = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{jk} \tag{13}$$

where (u_i, v_i) are location coordinates, x_{jk} are predictor values, and $\beta_k(u_i, v_i)$ are local regression coefficients.

Parameters are estimated locally using MLE with spatial weights based on distance using a bisquare kernel [18]:

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2, & d_{ij} < h \\ 0, & d_{ij} \geq h \end{cases} \tag{14}$$

where w_{ij} is the weight between points i and j, d_{ij} is the distance, and h is the bandwidth controlling spatial proximity. The optimal kernel is selected using AICc and the optimal weight

is determined by selecting the least value. The following is one way to express the AICc equation [19, 20].

$$\text{AICc} = \text{AIC} + \frac{2k(k+1)}{n-k-1} \tag{15}$$

with

$$\text{AIC} = 2k - 2\log(L), \tag{16}$$

where k denotes the number of predictor variables and L represents the likelihood function of the model. The Golden Search method is applied iteratively to obtain the minimum AICc within the range of observation locations.

2.2.5. Model Evaluation and Interpretation

The model's performance was evaluated using the Confusion Matrix and Apparent Error Rate (APPER) to measure prediction errors. Table 2 shows the misclassification counts for two groups:

Table 2: Misclassification

Actual Group	Estimated Group	Misclassified	Total
π_1	n_{1c}	$n_{1M} = n_1 - n_{1c}$	n_1
π_2	$n_{2M} = n_2 - n_{2c}$	n_{2c}	n_2

APPER is calculated as [21]:

$$\text{APPER} = \frac{n_{1M} + n_{2M}}{n_1 + n_2} \tag{17}$$

where $n_{.M}$ is the number of misclassified items and $n_{.c}$ is the number correctly classified.

Apart from APPER, another commonly used classification evaluation method is the receiver operating characteristic (ROC) curve along with the area under the curve (AUC). The receiver operating characteristic (ROC) curve, along with the area under the curve (AUC), serves as a fundamental metric for evaluating the performance of a classification model by quantifying its ability to distinguish between positive and negative classes through the relationship between true positive rates (sensitivity) and false positive rates [22]. An AUC value closer to 1.0 indicates excellent discriminative ability, whereas a value near 0.5 suggests performance no better than random guessing.

Model interpretation was performed by visualizing local parameter estimates on thematic maps, showing the spatial distribution of predictor effects on the probability of poverty across regencies/cities.

3. Results and Discussion

3.1. Descriptive Statistics

To examine the spatial distribution of poverty status in West Java Province in 2023, a visual analysis using a thematic map is presented in Fig. 1.

Fig. 1, indicates that poor areas (red) are concentrated in eastern, southeastern, southern, and central West Java, including Garut, Tasikmalaya, Pangandaran, Ciamis, Kuningan, Majalengka, and Sumedang, while western and some central regions, such as Bekasi, Bogor, Sukabumi, and Bandung, are non-poor (yellow). This indicates that poverty in West Java is not solely driven by unemployment, warranting further analysis of other contributing factors.

3.2. Global Logistic Regression Model

The initial step in global regression modeling is parameter estimation using the Newton-Raphson iterative method. The estimated parameters are presented in Table 3.

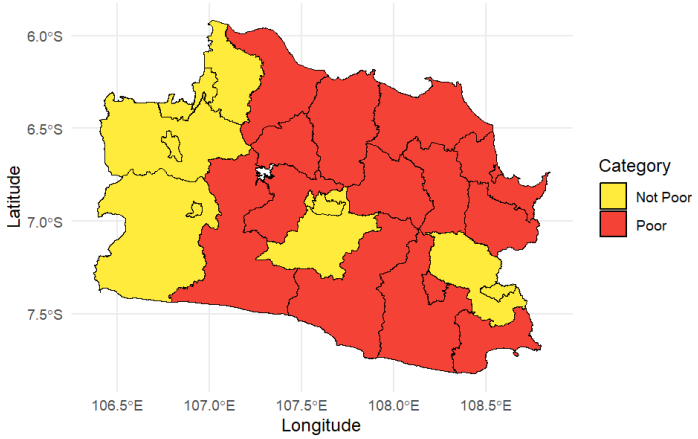


Fig. 1: Thematic Map of Poverty Status Distribution in West Java

Table 3: Parameter Estimates of the Global Binary Logistic Regression Model

Parameter	Estimate
β_0	26.370
β_1	6.23×10^{-7}
β_2	0.2993
β_3	8.57×10^{-4}
β_4	0.265
β_5	3.274

The next step is to conduct a simultaneous test of the parameters, with the following hypotheses:

$$H_0 : \beta_i = 0, \quad i = 1, 2, 3, 4, 5,$$
$$H_1 : \text{At least one } \beta_k \neq 0, \quad k = 1, 2, 3, 4, 5.$$

The decision rule is to reject H_0 if $G > \chi^2_{(\alpha;p)}$ at a significance level of $\alpha = 0.1$. Using statistical software, the test statistic was obtained as $G_{calc} = 9.490$, which is greater than $\chi^2_{(0.1;5)} = 9.230$, or equivalently, p-value $= 0.091 < \alpha = 0.1$. Thus, H_0 is rejected, indicating that all predictor variables jointly have a significant effect on poverty status in West Java Province.

Furthermore, partial tests were conducted to identify the individual contribution of each predictor variable to the response variable, with hypotheses:

$$H_0 : \beta_k = 0,$$
$$H_1 : \beta_k \neq 0, \qquad k = 1, 2, 3, 4, 5.$$

The decision rule is to reject H_0 if $|Z| > Z_{\alpha/2}$ or if the p-value $< \alpha = 0.1$. Based on the results, the variables Percentage of Households with Access to Safe Water (X_4) and Percentage of Households with Bamboo/Wooden Roofs (X_5) were found to have a significant individual effect on poverty status in West Java Province. In the global logistic regression model, the positive coefficients for (X_4) and (X_5) suggest that, at the provincial level, greater access to safe water and a higher share of households with bamboo or wooden roofs are both linked to a higher probability of poverty across West Java. This pattern suggests that these factors reflect broader provincial conditions such as rural settlement or unequal infrastructure that contribute to poverty across the region.

The global logistic regression model reached an accuracy of only 0.629 (90% CI: 0.453, 0.779) with precision of 0.647. This low accuracy and precision shows limited predictive power of this model. However, this model achieved an AUC of 0.789, which indicates a fair ability to distinguish between poor and non-poor households.

3.3. Spatial Assumption Test

Spatial assumptions are required to identify the presence of spatial dependence and spatial heterogeneity. In this study, Moran's I test and the Breusch-Pagan test were employed.

3.3.1. Moran's I Test for Spatial Dependence

To assess spatial dependence in the logistic regression model, the Moran's I test was conducted using the Pearson residuals of the global logistic regression model as the input variable based on equation (6). The test yielded a p-value of $0.005 < \alpha = 0.1$. Therefore, the null hypothesis (H_0) of spatial randomness is rejected, which is indicating that the residuals exhibit significant spatial autocorrelation. This finding suggests the presence of spatial dependence in the data and implying that observations located in close proximity tend to have similar residual values rather than being spatially independent.

3.3.2. Breusch-Pagan Test for Spatial Heterogeneity

To detect spatial heterogeneity, the Breusch-Pagan test was employed, as formulated in equation (5). Then, the test statistic yielded $\chi^2_{(0.1;5)} = 9.54 > 9.23$ and p-value $= 0.089 < 0.1$. Therefore, H_0 is rejected, indicating the presence of spatial heterogeneity in the data.

3.4. Geographically Weighted Logistic Regression Model

Selection of the GWLR model was carried out by determining the kernel weight based on the AICc value of each kernel based 15 as follows.

Table 4: Comparison of Kernel Weight Functions

Kernel	Bandwidth	AICc
Adaptive Bisquare	26	48.75
Fixed Bisquare	2.12	44.37

Based on Table 4, it is known that the Fixed Bisquare Weight is proven to be the best in modeling poverty in West Java in 2023 because it produces the lowest AICc compared to Adaptive Bisquare. The weight matrices obtained at each observation location are then used in the model formation process, resulting in a GWLR model that is local for each region. Parameter estimation in the Geographically Weighted Logistic Regression (GWLR) model is carried out through the Maximum Likelihood Estimator (MLE) approach, with an iterative solution using the Newton-Raphson algorithm. A summary of the descriptive statistics of the parameter estimation results is shown in Table 5 below.

Table 5: Summary of GWLR Parameter Estimation

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Range**
Intercept	31.095	6.013	24.689	45.208	20.519
X_1	-0.000007	0.000014	-0.000036	0.000012	0.000048
X_2	-0.485	0.432	-1.493	0.108	1.601
X_3	-0.000987	0.000301	-0.001534	-0.000416	0.00112
X_4	-0.285	0.038	-0.422	-0.236	0.185
X_5	3.766	0.555	3.255	5.194	1.939

Furthermore, an F-test is conducted to test simultaneously whether all predictor variables analyzed have a significant relationship with the response variable in the model. The simultaneous hypothesis test is as follows.

$$H_0 : \beta_1(u_i, v_i) = \beta_2(u_i, v_i) = \cdots = \beta_k(u_i, v_i) = 0$$

$$H_1 : \text{at least one } \beta_k(u_i, v_i) \neq 0$$

The decision rule is to reject H_0 if $G > \chi^2_{(\alpha,df)}$ or if the p-value $< \alpha = 0.1$. The calculated test statistic is $G_{calc} = 20.015 > \chi^2_{(0.1;11.793)} = 18.286$ or p-value $= 0.061 < 0.1$. This indicates that all independent variables simultaneously have a significant effect on poverty status in West Java Province.

In addition to simultaneous testing, a partial T-test is also conducted with the following hypotheses.

$$H_0 : \beta_k(u_{23}, v_{23}) = 0;\ k = 1, 2, 3, 4, 5$$

$$H_1 : \beta_k(u_{23}, v_{23}) \neq 0$$

The critical region for the partial test is to reject H_0 if $|Z| > Z_{0.05}$ or $|Z| > 1.64$. Based on calculations, it is known that Open Unemployment Rate (X_2), Population Density (X_3), Percentage of Households with Proper Water Access (X_4), and Percentage of Households with Bamboo/Wood Roofs (X_5) significantly affect poverty status in the districts/cities of West Java Province.

Table 6: Summary of Partial Significance Test Results

Significant Variable(s)	**Regency/City**
None	Ciamis, Cirebon, Kota Banjar, Kota Cirebon, Kuningan, Pangandaran
X_4	Kota Sukabumi, Sukabumi
X_5	Indramayu, Kota Bogor, Kota Tasikmalaya, Tasikmalaya, Majalengka
X_4 and X_5	Bandung, Bandung Barat, Cianjur, Garut, Kota Bandung, Kota Cimahi, Subang, Sumedang
X_2 and X_5	Bogor, Kota Depok
X_2, X_3, X_5	Kota Bekasi
X_3, X_4, X_5	Bekasi, Karawang, Purwakarta

Based on Table 6, the variable GRDP per capita (X_1) does not significantly affect poverty status in West Java Province. This is consistent with the study by [23] which used multiple linear regression to model poverty rates in Indonesia. The results show that the GRDP variable does not significantly affect poverty rates. This may occur because this indicator only reflects the average income of a region without fairly representing its distribution [24].

3.5. Model Interpretation and Evaluation

The next step is to analyze the prediction results of the GWLR model to compare them with the actual poverty data and to observe the distribution of significant variables in each regency/city through a thematic map.

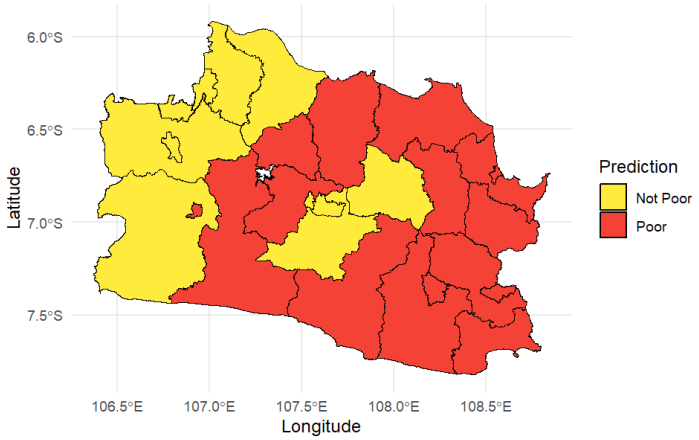


Fig. 2: Thematic Map of Predicted Poverty Status on West Java

Fig. 2 shows a prediction map of poverty status that differs from the data in Fig. 2, with changes in Ciamis, Banjar, and Sukabumi becoming "Poor", as well as Karawang and Sumedang becoming "Not Poor". To evaluate the prediction accuracy of the GWLR model, Table 7 presents the calculation of APPER and accuracy values. Based on 17, the APPER obtained by the GWLR model is 18.6%, with a model accuracy of 81.4% (90% CI: 0.644, 0.919).

Table 7: Confusion Matrix and Calculation of APPER and Accuracy

Category	**Prediction**	**APPER**	**Accuracy**	
	Non-Poor	Poor		
Non-Poor	9	3	(2+3)/27 = 0.186	0.814
Poor	2	13		

The thematic map showing the variables that significantly influence poverty status in each regency/city in West Java Province is presented in Fig. 3.

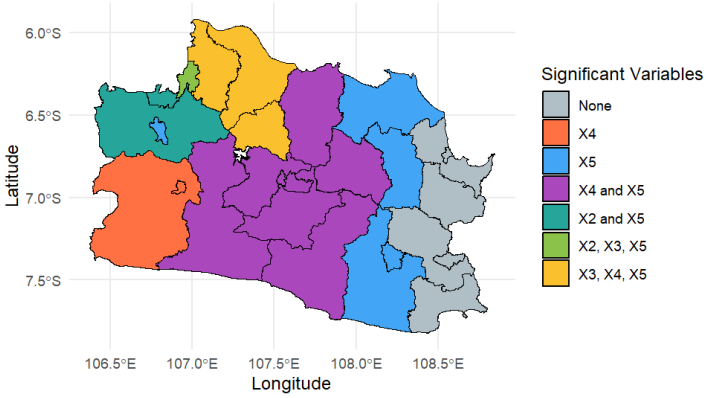


Fig. 3: Thematic Map of Significant Variables Distribution

Based on Fig. 3, which illustrates the distribution of predictor variables that significantly influence poverty status in the West Java Province, significant predictors include Open Unemployment Rate (X_2), Population Density (X_3), Percentage of Households with Access to Proper Water (X_4), and Percentage of Households with Roofs Made Predominantly of Bamboo or Wood (X_5). These four variables are significant and distributed across various regions, indicating that poverty in West Java is multidimensional and requires an intersectoral approach.

Only two regions, Sukabumi Regency and Sukabumi City, have a poverty status influenced solely by the percentage of households with access to adequate water (X_4). Limited access to clean water can hinder productive activities, thus reducing opportunities to escape poverty [25]. This situation reflects inequality and highlights the importance of equitable distribution of clean water services.

The regions in which poverty status is determined solely by the percentage of households with roofs made primarily of bamboo or wood (X_5) include the Indramayu Regency, the Majalengka Regency, the Tasikmalaya City, the Tasikmalaya Regency and Bogor City. A proper home is a basic need; therefore, the inability to afford it reflects low levels of income and welfare. This finding is consistent with Puteri and Notobroto [26], who concluded that the physical condition of a house, such as the type of roof, significantly influences the status of poverty. Roofs made from shingles or wood are associated with a higher risk of poverty compared to tile roofs.

Meanwhile, regions influenced by both the Percentage of Households with Access to Proper Water (X_4) and the Percentage of Households with Roofs Made Predominantly of Bamboo or Wood (X_5) include Bandung Regency, West Bandung Regency, Cianjur Regency, Garut Regency, Bandung City, Cimahi City, Subang Regency, and Sumedang Regency. These two significant

variables indicate that poverty in these areas is driven by limited access to fundamental human needs: clean water and adequate housing.

The regions influenced by two variables: Open Unemployment Rate (X_2) and Percentage of Households with Roofs Made Predominantly of Bamboo or Wood (X_5) include Bogor Regency and Depok City. The rise in unemployment and the use of bamboo or wooden roofs reflect economic constraints and substandard housing conditions, which reinforce poverty in these areas. This indicates that poverty is shaped by economic factors and unequal access to basic needs and infrastructure [27].

However, Bekasi City is influenced by three variables: Open Unemployment Rate (X_2), Population Density (X_3), and Percentage of Households with Roofs Made Predominantly of Bamboo or Wood (X_5). The relationship between roof types and poverty has been discussed previously. Meanwhile, [28] asserts that population density and unemployment significantly affect poverty, as high pressure on resources and limited job opportunities exacerbate poverty levels.

Other regions influenced by three variables are Population Density (X_3), Percentage of Households with Access to Proper Water (X_4), and Percentage of Households with Roofs Made Predominantly of Bamboo or Wood (X_5) include Bekasi Regency, Karawang Regency, and Purwakarta Regency. This illustrates that poverty in these regions is shaped by demographic factors and basic household infrastructure conditions.

Subsequently, the suitability and effectiveness of the GWLR model in modeling poverty in West Java will be analyzed, as presented in Table 8.

Table 8: Comparison of Global Logistic Regression and GWLR Models

Model	Deviance	Pseudo R^2	Accuracy	Precision	AUC
Global Logistic Regression	27.604	0.255	0.629	0.647	0.789
GWLR	20.015	0.460	0.814	0.812	0.933

Based on Table 8, the GWLR model performs better than the global logistic regression model. This conclusion is supported by five criteria: a lower deviance value, a higher pseudo R^2 value, accuracy, precision, and AUC value compared to the global logistic regression model.

4. Conclusion

The analysis revealed that in 2023, poverty remained a significant spatial issue in West Java Province, with 55.6% of regencies and cities categorized as poor. The Geographically Weighted Logistic Regression (GWLR) model with a Fixed Bisquare weighting scheme outperformed the global logistic regression model, as indicated by its lower deviance, higher pseudo R^2, accuracy, precision, and AUC value. Four variables which are Open Unemployment Rate (X_2), Population Density (X_3), Percentage of Households with Access to Proper Water Facilities (X_4), and Percentage of Households with Bamboo or Wooden Roofing (X_5) were found to have a significant influence on poverty status at the 10% significance level. The GWLR model achieved an accuracy rate of 81.4% and successfully classifying most regions but still showing misclassification in several areas.

This study has several limitations. First, the data used cover only a single year of observation, which may not fully represent the spatial and temporal dynamics of poverty. Second, several important factors, such as social indicators (e.g., educational attainment), were not considered in the model. Third, the GWLR model in this study employs only a single Bisquare kernel function with a uniform bandwidth, whereas each variable may require a different bandwidth. Therefore, future research is recommended to explore the use of variable-specific bandwidths and consider a temporal logistic regression model to better capture the spatial and temporal heterogeneity of poverty. These findings emphasize the need to account for local characteristics in poverty analysis and policy design and highlight that spatially adaptive strategies and improved basic infrastructure are essential for effective poverty reduction in West Java.

CRediT Authorship Contribution Statement

Toha Saifudin: Conceptualization, Methodology, Funding Acquisition, Writing-Review & Editing. **Nur Chamidah:** Conceptualization, Funding Acquisition. **Najwa Khoir Aldawiyah:** Investigation, Formal Analysis, Writing-Original Draft Preparation, Visualization. **Citrawani Marthabakti:** Investigation, Formal Analysis, Writing-Original Draft Preparation. **Aulia Ramadhanti:** Investigation, Data Curation, Writing-Original Draft Preparation, Resources, Writing-Review & Editing. **Muhammad Hafidzuddin Nahar:** Investigation, Writing-Original Draft Preparation, Writing-Review & Editing. **Nuafal Muzakki:** Investigation, Writing-Original Draft Preparation, Writing-Review & Editing.

Declaration of Generative AI and AI-assisted technologies

"Generative AI (ChatGPT version 4.0) was used in this manuscript for proofreading purposes."

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

The data and code supporting the findings of this study are available from the corresponding author upon reasonable request and subject to confidentiality agreements.

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