

MODELING GEOGRAPHICALLY WEIGHTED BETA REGRESSION ON POVERTY DATA IN INDONESIA

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ABSTRACT

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Poverty is a major development issue influenced by socioeconomic factors and regional disparities. Previous studies on poverty in Indonesia have largely employed global regression approaches that assume homogeneous relationships between explanatory variables and poverty across regions. This assumption may overlook spatial heterogeneity, resulting in less accurate estimates and limited relevance for local policymaking. Therefore, this study applies Geographically Weighted Beta Regression (GWBR) to model the proportion of the poor population in Indonesia and compares its performance with global beta regression. The independent variables are the Human Development Index, Open Unemployment Rate, Mean Years of Schooling, Life Expectancy, Literacy Rate, and Access to Safe Drinking Water. Parameter estimation was performed using Maximum Likelihood Estimation (MLE), while statistical inference was conducted through simultaneous and partial significance tests. Spatial dependence was assessed using Moran's *I* statistic. The main contribution of this study is the identification of spatially varying determinants of poverty using the GWBR approach, providing localized insights for more targeted poverty alleviation policies. The results indicate significant spatial autocorrelation in the residuals of the global beta regression model, suggesting that spatial effects should be considered in poverty analysis. Compared with the global beta regression model, GWBR demonstrated superior performance, yielding lower values of AIC (-909.462), AICc (-905.439), and MAAPE (0.218). Local parameter estimates revealed substantial spatial heterogeneity in the determinants of poverty. Life Expectancy was the most consistent factor, exhibiting a significant negative effect in 34 provinces, while Mean Years of Schooling showed a significant negative effect in 15 provinces. The effects of the remaining variables varied across regions, indicating that the determinants of poverty differ spatially across Indonesia. These findings suggest that GWBR more effectively captures local variations in the determinants of poverty and supports the development of region-specific poverty alleviation policies in Indonesia.



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1. INTRODUCTION

Poverty remains one of the most critical challenges in national development because it directly affects social welfare, economic growth, and quality of life [1]. Despite continuous government efforts to reduce poverty, substantial disparities persist across regions in Indonesia. According to the Badan Pusat Statistik (BPS), the national poverty rate increased from 9.22% in September 2019 to 10.19% in September 2020 during the COVID-19 pandemic before gradually declining to 8.57% in September 2024 [2]. However, this improvement has not been evenly distributed across provinces, indicating that the determinants of poverty may vary geographically [3]. Such regional differences suggest that spatial aspects should be considered when analyzing poverty-related issues in Indonesia [3].

Spatial heterogeneity refers to the condition in which relationships between variables differ across geographic locations due to variations in socioeconomic, demographic, environmental, and institutional characteristics [3]. Consequently, global statistical models that assume constant relationships across all observations may fail to adequately represent local characteristics and can lead to biased or inefficient parameter estimates [3]. [4].

Regression analysis is commonly used to examine the relationship between a response variable and a set of explanatory variables [4]. However, conventional methods such as Ordinary Least Squares (OLS) are not appropriate for modeling proportion data because the response variable is bounded between 0 and 1 and often violates the assumptions of normality and homoscedasticity [5]. Beta Regression addresses this limitation by assuming a Beta-distributed response variable, making it more suitable for modeling proportions such as the percentage of the poor population [6]. Nevertheless, Beta Regression is a global approach that assumes identical parameter values across all locations and therefore cannot accommodate spatial heterogeneity [6], [7].

To overcome this limitation, Geographically Weighted Regression (GWR) was developed to allow regression coefficients to vary across locations through spatial weighting [3],[8]. However, GWR assumes an unbounded continuous response variable and is therefore less suitable for proportion data. Geographically Weighted Beta Regression (GWBR) extends Beta Regression by incorporating geographically weighted estimation while maintaining the distributional characteristics of proportional data [10].

Several studies have demonstrated the advantages of spatial modeling in socioeconomic research [3], [8]. Studies employing GWR have shown that spatial models provide more accurate estimates and richer local information than global models [8], [9]. Furthermore, research applying GWBR to proportion data has reported improved model performance and better representation of spatially varying relationships [10]. However, most previous studies on poverty in Indonesia have relied on global regression approaches or conventional spatial models, while empirical applications of GWBR to poverty proportion data at the provincial level remain limited [11]. In addition, previous studies have rarely examined how the effects of key socioeconomic indicators differ across regions [11], [12].

Therefore, this study aims to fill this gap by applying Geographically Weighted Beta Regression to model the proportion of the poor population in Indonesia. The novelty of this research lies in the integration of spatial heterogeneity analysis with Beta Regression to identify region-specific determinants of poverty and evaluate their spatially varying effects. The explanatory variables considered include the Human Development Index, Open Unemployment Rate, Mean Years of Schooling, Life Expectancy, Literacy Rate, and Access to Safe Drinking Water. Furthermore, the performance of the GWBR model is compared with that of global Beta Regression. The findings are expected to provide a deeper understanding of regional disparities in poverty determinants and support the formulation of more targeted and effective poverty alleviation policies in Indonesia.

2. METHODS

Material and Data

The data in this study consist of numerical data. The numerical data in this study includes dependent variables such as the percentage of the poor population (Y) and independent variables such as the human development index (X_1), the open unemployment rate (X_2), the average years of schooling for the population aged 15 and older (X_3), life expectancy (X_4), the literacy rate for

the population aged 15 and older (X_5), and the percentage of households using safe drinking water sources (X_6). The data sources for this study were obtained from the website of the Badan Pusat Statistik (BPS). This study uses data from 2019–2025 for each province in Indonesia, while the software used is RStudio.

Research Method

This study employs a quantitative approach to analyze the spatial patterns of poverty across provinces in Indonesia using Global Beta Regression and Geographically Weighted Beta Regression (GWBR). The analysis covers all provinces in Indonesia and utilizes secondary data obtained from publications and databases of the Badan Pusat Statistik (BPS). The dataset consists of annual observations for the period 2019–2025 and was processed using RStudio software.

The response variable is the proportion of the poor population (Y). The explanatory variables consist of the human development index (X_1), the open unemployment rate (X_2), the average years of schooling for the population aged 15 and older (X_3), life expectancy (X_4), the literacy rate for the population aged 15 and older (X_5), and the percentage of households using safe drinking water sources (X_6). All variables are measured on a ratio scale in accordance with BPS definitions.

The analysis begins with descriptive statistics to identify the characteristics and distribution patterns of the variables. Prior to model estimation, multicollinearity among explanatory variables is examined using the Variance Inflation Factor (VIF), defined as:

$$VIF_j = \frac{1}{1 - R_j^2}$$

Where R_j^2 is the coefficient of determination obtained from regressing the j^{th} explanatory variable on all remaining explanatory variables. A variable is considered free from serious multicollinearity if its VIF value is less than 10.

As a baseline model, Global Beta Regression is estimated because the response variable is proportional data bounded within the interval (0,1). Let Y_i denote the proportion of the poor population in province (i). The response variable is assumed to follow a Beta distribution,

$$Y_i \sim Beta(\mu_i, \phi), \quad 0 < Y_i < 1$$

where μ_i represents the mean parameter of the response variable and ϕ denotes the precision parameter, which controls the variability of the Beta distribution. A larger value of ϕ indicates lower variance around the mean. Using the logit link function, the relationship between the mean response and the explanatory variables can be expressed as:

$$g(\mu_i) = \log\left(\frac{\mu_i}{1 - \mu_i}\right) = \beta_0 + \sum_{k=1}^p \beta_k x_{ki}, \quad i = 1, 2, \dots, n$$

where β_0 is the intercept and β_k represents the regression coefficient associated with the (k)-th explanatory variable. Model parameters are estimated using the Maximum Likelihood Estimation (MLE) method.

The overall significance of the model is evaluated using the Likelihood Ratio Test. The hypotheses are $H_0: \beta_1 = \beta_2 = \dots = \beta_p = 0$ and H_1 : at least one $\beta_k \neq 0, k = 1, 2, \dots, p$ with the test statistic:

$$G^2 = -2 \ln\left(\frac{L_0}{L_1}\right)$$

where L_0 and L_1 denote the likelihood values under the null and alternative hypotheses, respectively.

The significance of individual parameters is assessed using the Wald test:

$$Z_k = \left(\frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}\right)$$

where $\hat{\beta}_k$ is the estimated regression coefficient and $SE(\hat{\beta}_k)$ is its standard error.

Spatial dependence is examined using Moran's I statistic:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{S_0 \sum_{i=1}^n (y_i - \bar{y})^2}$$

where w_{ij} denotes the spatial weight between locations i and j , and $S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$. Spatial heterogeneity is evaluated using the Breusch–Pagan statistic:

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

A significant result indicates that the variance structure differs across locations, suggesting the presence of spatial heterogeneity.

To accommodate spatial heterogeneity, Geographically Weighted Beta Regression (GWBR) is employed. This model allows regression coefficients to vary by geographic location. The GWBR model is specified as:

$$g(\mu_i) = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) X_{ki}$$

where (u_i, v_i) denotes the geographic coordinates of location i , and $\beta_k(u_i, v_i)$ represents the local regression coefficient.

Spatial weights are determined using the Adaptive Bisquare Kernel function:

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

where d_{ij} is the Euclidean distance between locations i and j , and b_i denotes the adaptive bandwidth.

The optimal bandwidth is selected using the Cross-Validation (CV) criterion:

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

where $\hat{y}_{(-i)}$ is the predicted value obtained by excluding observation i from the estimation process.

Finally, model performance is compared using the Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc), and Mean Arctangent Absolute Percentage Error (MAAPE). These measures are defined as:

$$\begin{aligned} AIC &= -2 \ln(L) + 2k \\ AIC_c &= AIC + \frac{2k(k+1)}{n-k-1} \\ MAAPE &= \frac{1}{n} \sum_{i=1}^n \arctan \left(\left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \end{aligned}$$

where L denotes the maximized likelihood function, k is the number of estimated parameters, and n is the sample size. Lower values of AIC and AICc indicate a better balance between model fit and complexity. Furthermore, y_i represents the observed value and \hat{y}_i represents the predicted value. The MAAPE measures prediction accuracy, where smaller values indicate better predictive performance.

3. RESULTS

The results of the descriptive analysis of poverty rates in Indonesia indicate that the percentage of the poor population in Indonesia varies significantly across regions. The percentage of the poor population ranges from 0.037 to 0.268, with an average of 0.099. The data were then visualized using a histogram, yielding the distribution of the dependent variable as shown in the following figure:

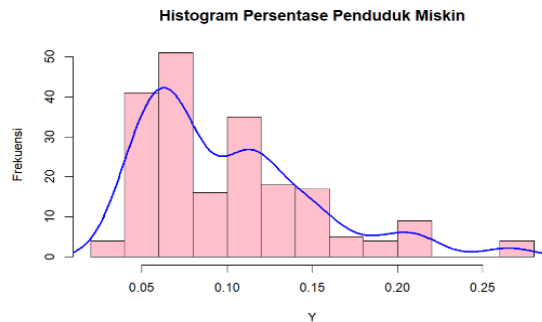


Figure 1. Histogram of Poverty Rates in Indonesia

Figure 1 shows that the percentage distribution of poverty rates in Indonesia is positively skewed. The data distribution is positively skewed, indicating that most provinces have low to moderate poverty rates, but there are some regions with relatively high poverty rates. The independent variables used in this study include the Human Development Index, Open Unemployment Rate, Average Years of Schooling, Life Expectancy, Literacy Rate, and Access to Safe Drinking Water. Descriptive statistical results indicate variations in social and economic characteristics across provinces in Indonesia. Before modeling, multicollinearity will be detected using the Variance Inflation Factor (VIF); the following are the results of the multicollinearity detection:

Table 1. Results of Multicollinearity Detection

Variable	VIF
Human Development Index	6,846
Open Unemployment Rate	1,538
Average Years of Schooling	4,789
Life Expectancy	5,097
Literacy Rate	2,168
Access to Safe Drinking Water	1,354

Based on the results of the multicollinearity test in Table 1, all variables have VIF values less than 10, indicating that there is no severe multicollinearity in the model. Next, a global beta regression model was constructed as an initial model to analyze the effect of independent variables on the percentage of the poor population. The results of the simultaneous test indicate that all independent variables collectively have a significant effect on the dependent variable with a p-value of $1.0622 \times 10^{-5} < 0.05$. In the partial tests, the variables Life Expectancy, Literacy Rate, and Access to Safe Drinking Water were found to have a significant effect, while the variables Human Development Index, Open Unemployment Rate, and Average Years of Schooling were not significant in the global model.

Spatial heterogeneity testing using the Breusch-Pagan test indicated the presence of spatial variation in the research data. Additionally, the results of the Moran’s I test on the residuals of the global beta regression model yielded a value of 0.927 with a p-value = $3.970 \times 10^{-87} < 0.05$, indicating the presence of strong positive spatial autocorrelation. This suggests that the global model has not been able to capture spatial variation optimally, thus requiring a spatial approach such as Geographically Weighted Beta Regression (GWBR).

GWBR modeling is performed by selecting the optimal kernel function and bandwidth based on the smallest Cross Validation (CV) value. In this study, testing will be conducted on two methods, namely Adaptive Bisquare (adaptive_bsq) and Fixed Bisquare (fixed_bsq); the selection table is as follows:

Table 2. Selection of Kernel Functions and Optimal Bandwidth

Method	Bandwidth	CV Value
Adaptive Bisquare (adaptive_bsq)	101,00	1156,894
Fixed Bisquare (fixed_bsq)	880,78	1136,450.

The results of the selection indicate that the fixed bisquare kernel function with a bandwidth of 880.78 is the best model. Local parameter estimates for the GWBR model show that the influence of each variable varies across regions. The following is a map of parameter estimates for the Geographically Weighted Beta Regression (GWBR) model:

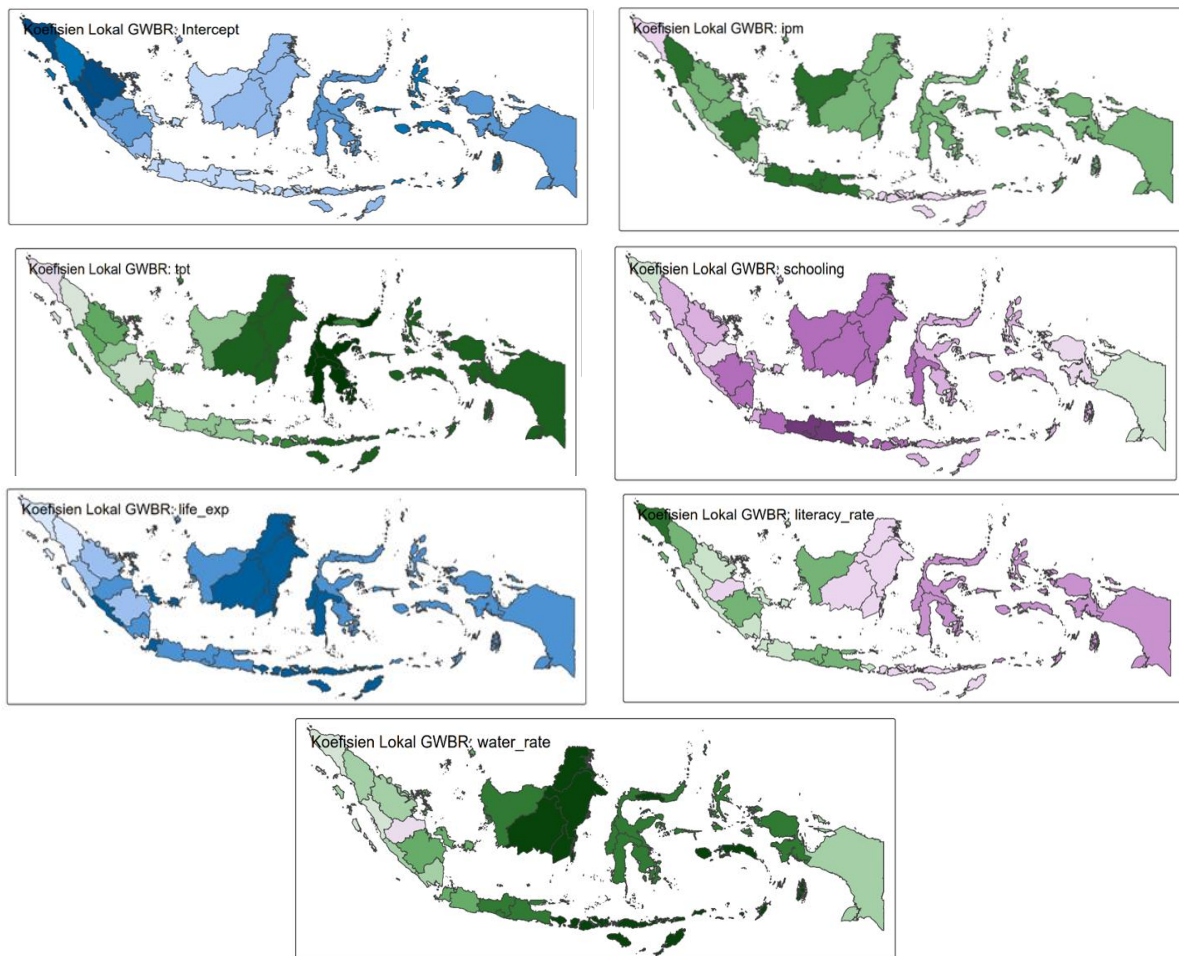


Figure 2. Plotting the Estimated GWBR Model Parameters

A local parameter significance test was conducted on the Geographically Weighted Beta Regression (GWBR) model to provide more detailed information regarding the spatial variation in the effects of the explanatory variables. Next, the results of the local parameter significance test will be explained for each independent variable based on the distribution maps obtained.

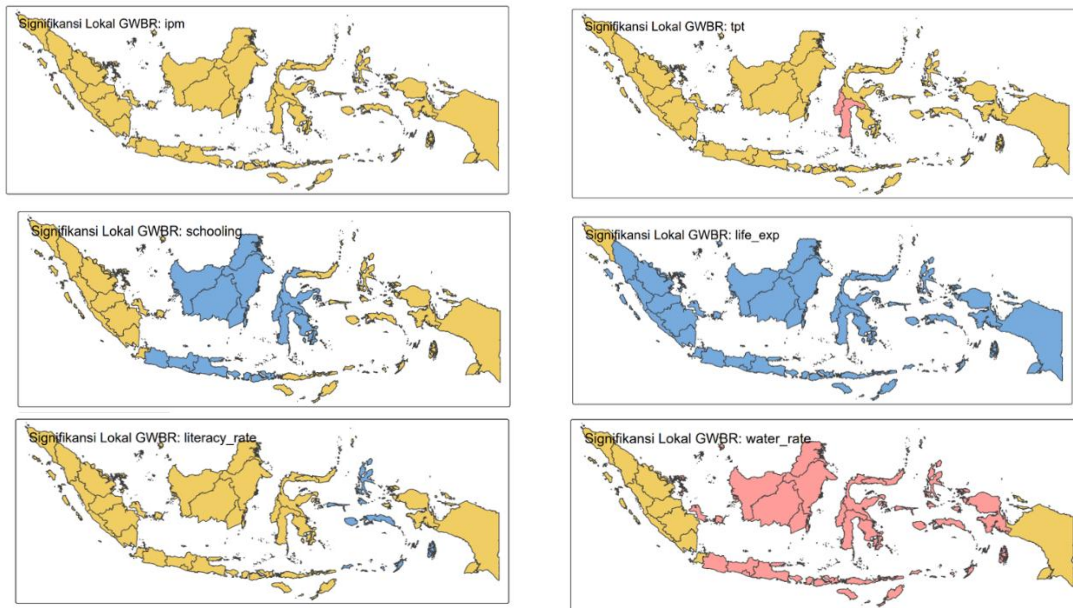


Figure 3. Mapping of the Significance of Local Parameters in the GWBR Model

Notes:

- Red indicates a significant positive result
- Blue indicates a significant negative result
- Yellow indicates no significant result

The life expectancy variable generally has a negative effect on poverty rates in nearly all provinces, meaning that an increase in life expectancy tends to reduce poverty. The average years of schooling variable also shows a negative effect in most regions, although this effect is significant only in certain provinces. Meanwhile, the effects of literacy rates and access to safe drinking water exhibit varying patterns across regions, both in terms of direction and magnitude of the effect

Mapping of poverty levels in Indonesia was conducted based on the results of global beta regression and Geographically Weighted Beta Regression (GWBR) models to illustrate the spatial distribution of poverty across regions. In addition, a comparison of the performance of the two models was conducted using the AIC, AICc, and MAAPE criteria to determine the most optimal model for explaining and predicting poverty levels. The following are the results of poverty mapping in Indonesia using the Global Beta Regression Model and the GWBR model.

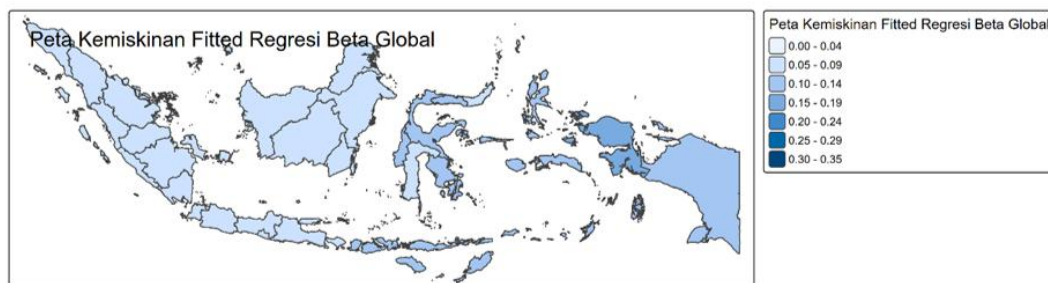


Figure 4. Poverty mapping in Indonesia using the Global Beta Regression Model

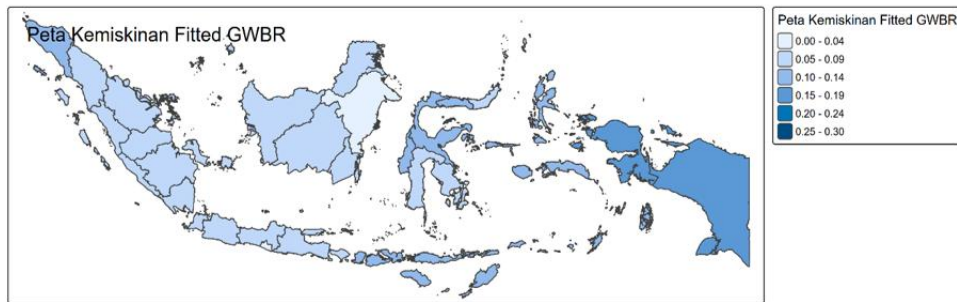


Figure 5. Poverty mapping in Indonesia using the GWBR Model

The model mapping results show that higher poverty rates tend to be concentrated in eastern Indonesia, particularly in Papua and several surrounding regions, while western Indonesia tends to have lower poverty rates. Compared to the global beta regression model, the GWBR model produces a more detailed spatial pattern and is able to capture local variations across regions.

The comparison between the Global and GWBR models uses several criteria, namely the Akaike Information Criterion (AIC), the Corrected Akaike Information Criterion (AICc), and the Mean Absolute Percentage Error (MAAPE). The following are the results of the comparison test between the two models:

Table 3. Comparison of Global Beta Regression and GWBR

Model	AIC	AICc	MAAPE
Global Beta Regression	-837,688	-836,935	0,260
GWBR	-909,462	-905,439	0,218

Based on a comparison of the Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc), and Mean Absolute Percentage Error (MAAPE) values, the GWBR model performed better with an AIC of -909.462, an AICc of -905.439, and a MAAPE of 0.218. These values are better than those of the global beta regression model, which has an AIC of -837.688, an AICc of -836.935, and a MAAPE of 0.260. Thus, the GWBR model is considered more effective in modeling poverty in Indonesia because it is able to accommodate spatial heterogeneity and provide more accurate local information.

In addition to model performance, parameter significance testing was conducted to identify the determinants of poverty at the provincial level. The results reveal substantial spatial variation in the significance of explanatory variables, indicating that the effects of socioeconomic factors differ across regions. Life Expectancy X_4 was identified as the most influential variable, exhibiting a significant negative effect in 34 provinces. This finding suggests that improvements in health conditions and longevity are consistently associated with lower poverty levels throughout Indonesia. Mean Years of Schooling X_3 also showed a significant negative effect in 15 provinces, indicating that higher educational attainment contributes to poverty reduction through increased human capital and employment opportunities.

Access to Safe Drinking Water X_6 was found to be significant in 24 provinces, highlighting the importance of basic infrastructure and access to essential services in influencing regional poverty conditions. In contrast, the Open Unemployment Rate X_2 and Literacy Rate X_5 were significant in only two provinces each, suggesting that their impacts are highly location-specific. Meanwhile, the Human Development Index X_1 did not exhibit a significant local effect in any province. These findings confirm the presence of spatial heterogeneity and demonstrate that the determinants of poverty vary across regions.

Overall, the results indicate that GWBR not only outperforms the global beta regression model in terms of goodness-of-fit and predictive accuracy but also provides detailed local information regarding the factors influencing poverty in each province. Therefore, GWBR is more suitable for modeling poverty in Indonesia and can serve as a valuable tool for developing region-specific poverty alleviation policies.

4. DISCUSSIONS

The results of this study indicate that the proportion of the poor population in Indonesia exhibits significant spatial variation across provinces. The presence of spatial autocorrelation and spatial heterogeneity demonstrates that the relationship between the explanatory variables and poverty is spatially non-stationary, indicating that the effects of socioeconomic factors differ across regions. Consequently, a global regression model is insufficient to adequately represent regional poverty conditions because it assumes homogeneous relationships between variables across all provinces. This finding is consistent with the concept of spatial heterogeneity in geographically weighted modeling, which emphasizes that local characteristics should be incorporated into spatial analyses [3], [4].

The Geographically Weighted Beta Regression (GWBR) model outperformed the global Beta Regression model by accommodating spatial heterogeneity through the estimation of location-specific parameters. The lower AIC, AICc, and MAAPE values obtained by the GWBR model indicate superior model fit and predictive performance. These findings demonstrate that incorporating local spatial effects substantially improves the ability to explain regional poverty patterns. Similar results have been reported in recent studies applying geographically weighted approaches to poverty analysis in Indonesia, which consistently found that local spatial models provide more accurate estimates and richer regional information than global regression models [13], [14].

Among the explanatory variables, Life Expectancy exhibited a significant negative effect in almost all provinces, indicating that improvements in public health contribute to poverty reduction. Better health conditions increase labor productivity, improve employment opportunities, and enhance household welfare. This finding is consistent with the study conducted by Alwansyah [13], who reported that human development indicators are closely associated with poverty levels in Indonesia. Similar evidence has also been reported in recent spatial studies, which found that health-related indicators exhibit spatially varying effects and play an important role in explaining regional socioeconomic disparities [15].

The Open Unemployment Rate was statistically significant only in several provinces, including West Sulawesi and South Sulawesi. This result suggests that unemployment is not the dominant determinant of poverty in every region. In several provinces, poverty is likely influenced by other factors such as employment quality, labor productivity, the informal sector, and access to economic opportunities. Similar conclusions were reported by Ramadayani et al. [16], who found that the socioeconomic effects of unemployment differ across regions because of variations in local economic structures.

The effects of Literacy Rate and Access to Safe Drinking Water also varied spatially. Literacy Rate significantly reduced poverty in several eastern provinces, particularly Maluku and North Maluku, indicating that basic literacy remains essential for improving educational attainment, employment opportunities, and household welfare. Meanwhile, Access to Safe Drinking Water exhibited significant effects in most provinces, emphasizing the importance of basic infrastructure and environmental quality in supporting socioeconomic development. Recent studies have likewise highlighted the contribution of infrastructure and public services to regional poverty reduction and human development outcomes [17], [18].

Overall, the findings of this study confirm that GWBR provides a more comprehensive representation of poverty patterns than the global Beta Regression model because it simultaneously accounts for the bounded nature of proportional data and spatial heterogeneity. By estimating local regression coefficients, GWBR is capable of identifying regional differences that cannot be captured by conventional global models. However, several explanatory variables, including the Human Development Index and Mean Years of Schooling, were not statistically significant in many provinces. This finding suggests that poverty is influenced by complex interactions among socioeconomic, demographic, and institutional factors that may not be fully represented by the variables included in the present study.

The findings have important policy implications. Poverty alleviation strategies in Indonesia should adopt a region-specific rather than a uniform national approach. Provinces where health indicators exert significant effects should prioritize investments in healthcare services and public

health programs. Conversely, provinces where unemployment significantly influences poverty require policies aimed at expanding employment opportunities, improving workforce skills, and strengthening local economic development. Likewise, interventions related to education and basic infrastructure, particularly access to safe drinking water, should be tailored to the socioeconomic characteristics of each province to maximize policy effectiveness.

From a methodological perspective, this study demonstrates that GWBR provides a more comprehensive framework for modeling poverty proportion data than global Beta Regression because it simultaneously accommodates the bounded nature of the response variable and spatial heterogeneity. Therefore, this approach has considerable potential for application in other socioeconomic studies involving spatially varying relationships. Future studies should incorporate additional explanatory variables related to regional economic development, income inequality, government expenditure, infrastructure, and social protection programs. Furthermore, comparisons with other spatial regression approaches, such as the Spatial Lag Model (SLM), Spatial Error Model (SEM), and Geographically Weighted Panel Regression (GWPR), provide a more comprehensive evaluation of spatial modeling techniques for poverty analysis.

5. CONCLUSION

The results indicate that the proportion of the poor population in Indonesia exhibits substantial spatial variation across regions. Descriptive and spatial exploratory analyses revealed the presence of spatial autocorrelation and spatial heterogeneity, suggesting that a global regression model is insufficient to capture regional differences in poverty determinants. These findings indicate that each province has distinct socioeconomic characteristics influencing poverty levels.

The Geographically Weighted Beta Regression (GWBR) model effectively accommodates these spatial variations by estimating local parameters for each province. The effects of the Human Development Index, Open Unemployment Rate, Mean Years of Schooling, Life Expectancy, Literacy Rate, and Access to Safe Drinking Water vary spatially, confirming the non-stationary nature of poverty determinants. Among these variables, Life Expectancy was the most influential, showing significant effects in 34 provinces, followed by Access to Safe Drinking Water (24 provinces) and Mean Years of Schooling (15 provinces). These results emphasize the importance of region-specific poverty alleviation policies.

Model comparison shows that GWBR outperforms the global beta regression model, as evidenced by lower AIC, AICc, and MAAPE values, indicating its superior ability to capture spatial heterogeneity and local characteristics. Future research should incorporate additional socioeconomic variables and compare GWBR with other spatial regression models, such as Spatial Lag Models (SLM) and Spatial Error Models (SEM), while also exploring alternative kernel functions and bandwidth selection methods to further improve model performance.

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7. REFERENCES

- [1] World Bank, *Poverty and Shared Prosperity 2022: Correcting Course*. Washington, DC, USA: World Bank, 2022.
- [2] Badan Pusat Statistik, *Profil Kemiskinan di Indonesia September 2024*. Jakarta, Indonesia: Badan Pusat Statistik, Jan. 2025.
- [3] R. Yang, "Geographically Weighted Regression: A Scoping Review and Future Directions," *Land*, vol. 15, no. 6, Art. no. 915, 2026.
- [4] M. N. Lessani, A. Comber, P. Harris, and B. Lu, "SGWR: Similarity and Geographically Weighted Regression," *International Journal of Geographical Information Science*, vol. 38,

- no. 8, pp. 1800–1825, 2024.
- [5] J. Fox, *Applied Regression Analysis and Generalized Linear Models*, 4th ed. Thousand Oaks, CA, USA: SAGE Publications, 2024.
 - [6] S. L. Ferrari and F. Cribari-Neto, "Beta Regression for Modelling Rates and Proportions," *Journal of Applied Statistics*, vol. 31, no. 7, pp. 799–815, 2004.
 - [7] I. Kosmidis and A. Zeileis, "Extended-Support Beta Regression for [0,1] Responses," *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, vol. 74, no. 1, pp. 1–28, 2025.
 - [8] F. Cribari-Neto and A. Zeileis, "Beta Regression in R," *Journal of Statistical Software*, vol. 34, no. 2, pp. 1–24, 2010.
 - [9] I. Kosmidis and A. Zeileis, "Extended-Support Beta Regression for [0,1] Responses," *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, vol. 75, no. 1, pp. 139–157, 2026.
 - [10] R. F. da Silva and F. Cribari-Neto, "Geographically Weighted Beta Regression for Modeling Spatial Rates and Proportions," *Journal of Applied Statistics*, vol. 41, no. 12, pp. 2519–2537, 2014.
 - [11] L. Anselin, *Spatial Econometrics: Methods and Models*. Dordrecht, The Netherlands: Kluwer Academic Publishers, 1988.
 - [12] L. Anselin, **Modern Spatial Econometrics in Practice: A Guide to GeoDa, GeoDaSpace and PySAL**. Chicago, IL, USA: GeoDa Press LLC, 2024.
 - [13] M. A. Alwansyah, "Pemodelan Regresi Beta pada Data Kemiskinan di Indonesia," Master's thesis, Statistics Study Program, Faculty of Mathematics and Natural Sciences, Universitas Bengkulu, Bengkulu, Indonesia, 2024.
 - [14] H. P. Faradiba and A. S. Duhri, "Using the Geographically Weighted Regression (GWR) Method to Find Out the Factors Causing Poverty in North Sumatra Province," *International Journal of Science and Mathematics Education*, vol. 1, no. 1, pp. 18–28, 2024.
 - [15] N. Miftakhurriza et al., "Geographically Weighted Panel Regression Modeling on Life Expectancy Rate in South Sulawesi," *Parameter: Journal of Statistics*, vol. 4, no. 2, pp. 93–102, 2024.
 - [16] M. R. Ramadayani, F. H. Indiyah, and I. Hadi, "Pemodelan geographically weighted regression menggunakan pembobot kernel fixed dan adaptive pada kasus tingkat pengangguran terbuka di Indonesia," *JMT: Jurnal Matematika dan Terapan*, vol. 4, no. 1, pp. 51–62, 2022.
 - [17] A. Sulistiyowati, M. Masjkur, and B. Susetyo, "Application of the Spatial Durbin Panel Model and Geographically Weighted Panel Regression on Poverty Data in West Java Province," *Indonesian Journal of Statistics and Its Applications*, vol. 9, no. 2, pp. 240–260, 2025.
 - [18] S. Widodo, "The Effect of Access to Suitable Drinking Water, Health Budget, and Other Factors on Life Expectancy in Indonesia," *Jurnal Budget*, 2025.