Comparison of Geographically Weighted Regression (GWR) and Mixed Geographically Weighted Regression (MGWR) Models on the Poverty Levels in Central Java in 2023

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Abstract—**Poverty is considered a serious global issue that must be immediately eradicated by Sustainable Development Goals (SDGs) 1, namely ending poverty anywhere and in any form. As a developing country, poverty is a complex issue faced by Indonesia. Tackling poverty in Indonesia has become a key focus of the government's strategic priorities. This issue of poverty is experienced by all provinces in Indonesia, including Central Java. The poverty rate in Central Java stands at 10.77% or 3.79 million people. The causes of poverty are explained by several factors. Using these various factors, a mapping model can be conducted to determine the number of poor populations in Central Java. This research employs Geographically Weighted Regression (GWR) and Mixed Geographically Weighted Regression (MGWR) approaches to compare the effectiveness of these models in analyzing the number of poor populations in Central Java in 2023. The kernel function weighting used in this study is Fixed Gaussian. The results showed that the MGWR model outperformed both the OLS regression and GWR models, achieving an Akaike Information Criterion (AIC) of 62.766, an R^2 of 82.3%, and a Mean Squared Error (MSE) of 0.177. Consequently, it can be inferred that the MGWR model was more suitable for explaining the poverty levels in Central Java.**

Index Terms—**Poverty Levels, Spatial Analysis, GWR, MGWR, Central Java Province.**

I. Introduction

THE rapid economic growth, accompanied by technological advancements and globalization, has significantly impacted income distribution across various countries. Despite substantial economic progress in certain regions, significant challenges related to social inequality persist, particularly in terms of income disparity and poverty levels [1]. Poverty is considered a serious global issue that must be immediately eradicated by Sustainable Development Goals (SDGs) 1, namely ending poverty anywhere and in any form [2]. As a developing country, poverty is a complex issue faced by Indonesia [4]. Tackling poverty in Indonesia has become a key focus in the government's strategic priorities, as highlighted in the National Long-Term Development Plan [3]. This issue of poverty is experienced by all provinces in Indonesia, including Central Java. According to the Central Java Central Bureau of Statistics on March 2023 [5], the poverty rate in Central Java reached 10.77% or 3.79 million people. Several factors explain the causes of poverty, including work productivity, economic growth, income inequality, income per capita, health facilities and services, nutrition, infant mortality rates, disease outbreaks, etc [6]. Using these various factors, a mapping model can be conducted to determine the number of poor populations in Central Java. In reality, the number of poor people in Indonesia is not homogeneous, and geographical factors, social conditions, economics, and other factors can influence it. Therefore, this condition can result in spatial heterogeneity. Modelling can be performed using Geographically Weighted Regression (GWR) and Mixed Geographically Weighted Regression (MGWR).

Many studies have discussed poverty. Research conducted by He et al. stated that addressing the root causes of poverty is a critical area of research and policy, and they found a notably significant relationship between poverty and geographic factors [7]. Research conducted by Miranti explores the factors related to disparities in regional poverty, concluding that the type of income growth significantly impacts poverty reduction [8]. Meanwhile, research by Friedman indicates that poverty is influenced by average income growth and inequality. [9] to [10]. Other studies state the causes of poverty may be explained by several factors: work productivity, economic growth, income inequality, income per capita, health facilities and services, nutrition, infant mortality rates, disease outbreaks, etc [6].

Of the several studies about poverty, no one considered comparing GWR and MGWR models. This research aims to assist the Central Java Government in formulating recommendations for the regency or city governments regarding what needs to be improved to reduce poverty. Decisions based on the results of comparisons using GWR and MGWR modelling in analyzing poverty levels in Central Java in

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2023. By understanding the performance differences between the two models, this research seeks to make a significant contribution to understanding the poverty in Central Java for the government and the society. Hence, they can collaborate to alleviate poverty. In GWR modelling, we use a fixed Gaussian kernel. Lumbantoruan et al. previously applied a fixed Gaussian kernel in their GWR model for poverty modelling in Papua, achieving an R^2 value of approximately 88% [11]. In this research, we used MGWR 2.2 software, and performance can be seen in the study conducted by Liu et al. [12]. The steps for using the application and the graphical user interface (GUI) are presented in the study by Oshan et al. [13].

II. Model Formulations

A. Ordinary Least Square

Ordinary Least Squares (OLS) linear regression is a statistical approach commonly employed to analyze the relationship between a dependent variable and multiple explanatory variables [14].

$$y_i = \beta_0 + \beta_1 x_1 + \beta_n x_n + \mathrm{e} \tag{1}$$

In this equation, y_i represents the observed value of the dependent variable, β_0 is the estimated intercept, indicating the value of y when x is zero. The parameter β_1 corresponds to the estimate for x_1, while x_n represents the explanatory variables, and β_n are the regression coefficients that signify how much the dependent variable y changes for each one-unit increase in x.

The variance inflation factor (VIF) is utilized to evaluate the degree of multicollinearity in the regression model [14]. The variance inflation factor (VIF) is calculated using the following formula [15].

$$\text{VIF} = \frac{1}{1 - R^2} \tag{2}$$

VIF value greater than 10 for any explanatory variable suggests a high level of multicollinearity, indicating that the variable may need to be excluded from the model.

B. Heterogeneity Test

The Breusch-Pagan Test serves as a statistical measure for detecting spatial heterogeneity. The hypothesis of the Breusch-Pagan test is a follows [16]:
H_0: $\sigma_1^2 = \sigma_2^2 = \ldots = \sigma_n^2 = \sigma^2$ (homoscedasticity)
H_1: At least one $\sigma_i^2 \neq \sigma^2$ (heteroscedasticity)
The test statistic is given by:

$$BP = \frac{1}{2}\left[\mathbf{f}^T \mathbf{Z}(\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{f}\right] \sim \chi_p^2 \tag{3}$$

If the Breusch-Pagan value is greater than $\chi^2_{\alpha,k+1}$, then H_0 is rejected, signaling the existence of spatial heterogeneity.

C. Geographically Weighted Regression (GWR)

The mathematical representation of the GWR model resembles that of a varying-parameter regression, where the parameters are considered to be functions based on the locations where the observations are collected [17]. The GWR model is a follows:

$$y_i = \beta_0(u_i, v_i) + \sum \beta_k(u_i, v_i) x_{ik} + \varepsilon \tag{4}$$

where (u_i, v_i) are the latitude and longitude coordinates of the i-th geographic location, β_k is the coefficient value of the k-th parameter ($k = 1, \ldots, p$), and x_{ik} is the k-th explanatory variable at the i-th location ($i = 1, 2, \ldots, n$).

Estimation of the GWR model parameters is conducted using the Weighted Least Square (WLS) method, which provides spatial weights to represent the location of observation data with each other. The parameter estimation is as follows:

$$\hat{\beta}(u_i, v_i) = \left[\mathbf{X}^T W(u_i, v_i) \mathbf{X}\right]^{-1} \mathbf{X}^T W(u_i, v_i) \mathbf{y} \tag{5}$$

where $W(u_i, v_i)$ is an $n \times n$ matrix with diagonal spatial weights at the i-th location.

D. Mixed Geographically Weighted Regression (MGWR)

Mixed Geographically Weighted Regression (MGWR) results from integrating multiple linear regression with Geographically Weighted Regression (GWR) models [18]. The foundation for forming the MGWR model is based on the concept that specific regression coefficients are fixed globally while others vary geographically [18]. In the MGWR model with p predictor variables, there is a q predictor variable with global characteristics, and $(p - q)$ predictor variables are local, where i represents the observation location. The general form of the MGWR is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{q} \beta_j(u_i, v_i) x_{ij} + \sum_{j=q+1}^{p} \beta_j x_{ij} + \varepsilon_i \tag{6}$$

where y_i, $\beta_0(u_i, v_i)$, and ε_i are the values of the response variable, constant/intercept, and residual at location i, respectively. Here, x_{ij} represents the value of predictor variable j at the location i. The spatial coordinates at location i are represented by (u_i, v_i). The variable β_j explains the regression coefficient of the global variable, while the variable $\beta_j(u_i, v_i)$ explains the regression coefficient of the local variable x_j at location i [19].

Similar to the GWR model, the MGWR model performs parameter estimation using the Weighted Least Squares (WLS) method. The steps involved in calculating WLS begin by forming a weighting matrix for each observation location. The parameter estimation for the MGWR model is as follows:

$$\begin{aligned}\hat{\beta}_g = &\left[X_g^T (I - S_l)^T (I - S_l) X_g\right]^{-1} \\ &\cdot X_g^T (I - S_l)^T (I - S_l) y\end{aligned} \tag{7}$$

$$\begin{aligned}\hat{\beta}_l(u_i, v_i) = &\left[X_l^T W(u_i, v_i) X_l\right]^{-1} X_l^T \\ &\cdot W(u_i, v_i)(y - X_g \hat{\beta}_g)\end{aligned} \tag{8}$$

where

$$\begin{aligned}S_l = &(x_{l1}^T [X_l^T W(u_i, v_i) X_l]^{-1} X_l^T \\ &\cdot W(u_i, v_i) + x_{l2}^T [X_l^T W(u_i, v_i) X_l]^{-1})\end{aligned} \tag{9}$$

and

$$S_g = X_g [X_g^T X_g]^{-1} X_g^T \tag{10}$$

III. Data Description and Algorithm Introduction

A. Data Description

The dataset used in this research consists of the number of poor populations in each regency or city in Central Java, which serves as the response variable Y. There are 36 records, representing the total number of regions in Central Java, with four predictor variables: open unemployment rate (X_1), life expectancy (X_2), percentage of population (X_3), and average years of schooling (X_4). This dataset was collected in 2023.

B. Spatial Regression Algorithm

The following are the steps taken to model the data on the number of poor populations using the GWR and MGWR models:

Step 1: Describe the number of poor populations and relevant variables in each regency or city in Central Java with descriptive statistics. Here is an overview of the dataset and the lowest or highest data.

Step 2: Mapping data on the number of poor populations in each regency or city in Central Java. From this map, the proximity of the relationships between neighbouring regions or cities can be seen.

Step 3: Standardise the data using the Z-score. Liu et al. explain the Z-score formula in detail [20].

This research presents the relationship between the number of poor populations Y and independent variables (X_1, X_2, X_3, X_4) as a line of best fit. The OLS model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \mathrm{e} \qquad (11)$$

Where Y represents the number of individuals living in poverty, β_0 denotes the estimated intercept, which signifies the value of Y when X is zero, β_1 corresponds to the parameter estimate for X_1, β_2 is the parameter estimate for X_2, β_3 is the parameter estimate for X_3, and β_4 is the parameter estimate for X_4.

Step 5: Test the assumption of spatial effect, namely, the heterogeneity test with the Breusch-Pagan test, on the data of the number of poor populations in Central Java. If the heterogeneity test results show spatial heterogeneity, then analysis can proceed to GWR modelling.

Step 6: Conduct data on the number of poor populations using GWR models. The GWR analysis involves the following steps [11]:

- Determine the best global regression model using the Ordinary Least Squares (OLS) approach (Step 4).
- Assess spatial heterogeneity by applying the Breusch-Pagan test (Step 5).
- Identify the optimal bandwidth utilizing a fixed Gaussian kernel weighting function.
- Establish the GWR model and evaluate the significance of the GWR coefficients.

The GWR model inputs are presented using MGWR 2.2 software as shown in TABLE I.

TABLE I
GWR Models with MGWR 2.2

GWR Models with MGWR 2.2
Input: Y, longitude, latitude, X_1, X_2, X_3, X_4
Output: residual OLS, $\hat{y}$ GWR, local R^2, β_0, β_1, β_2, β_3, β_4, se(β_0), se(β_1), se(β_2), se(β_3), se(β_4), p-value (β_0), p-value (β_1), p-value (β_2), p-value (β_3), p-value (β_4)
GWR Mode: GWR
Spatial Kernel: Fixed Gaussian
Bandwidth Searching: Golden section
Model Type: Gaussian
Optimization Criterion: AICc

Step 7: Conduct a spatial variability test to determine whether or not variables that do not have a significant effect.

Step 8: Conduct data on the number of poor populations using MGWR models. The steps of MGWR models are define local and global variable and determine the MGWR model. The MGWR model inputs are presented using MGWR 2.2 software as shown in TABLE II.

TABLE II
MGWR Models with MGWR 2.2

MGWR Models with MGWR 2.2
Input: Y, longitude, latitude, X_1, X_2, X_3, X_4
Output: residual OLS, $\hat{y}$ GWR, local R^2, β_0, β_1, β_2, β_3, β_4, se(β_0), se(β_1), se(β_2), se(β_3), se(β_4), p-value (β_0), p-value (β_1), p-value (β_2), p-value (β_3), p-value (β_4)
GWR Mode: MGWR
Spatial Kernel: Fixed Gaussian
Bandwidth Searching: Golden section
Model Type: Gaussian
Optimization Criterion: AICc

Step 7: Determine the best models using linear regression, GWR, and MGWR using AIC, R^2, and MSE. The research methodology employed in this study is shown in Fig. 1.

IV. Results and Analysis

A. Statistics Descriptives

To provide an overview of the dataset, TABLE III presents the descriptive statistics for the data.

TABLE III
Summary Statistics of Variables

Variable	Mean	Min.	Max.	Q1	Q2	Q3
Y (thousand)	108.33	7.45	286.14	75.66	97.48	143.34
X_1	4.87	1.92	8.98	3.95	4.57	5.88
X_2	75.55	73.95	77.93	74.54	75.04	76.47
X_3	2.86	0.02	11.74	2.05	2.69	3.45
X_4	8.26	6.40	11.24	7.37	7.86	9.13

Where Y is the number of poor populations, X_1 is the open unemployment rate, X_2 is the life expectancy, X_3 is the population percentage, and X_4 is the average years of schooling. Based on Table III, the lowest number of poor populations is 7,450, while the highest is 286,140. With such a large difference, addressing regencies or cities with many poor populations is necessary. Moreover, by 2023, Central Java Province will have Indonesia's third-highest number of poor people. The maximum open unemployment rate has reached 8.98%, far exceeding the national open unemployment rate of 5.32%. In Central Java, life expectancy is 75.55 years, surpassing the national average of 72.32 years.

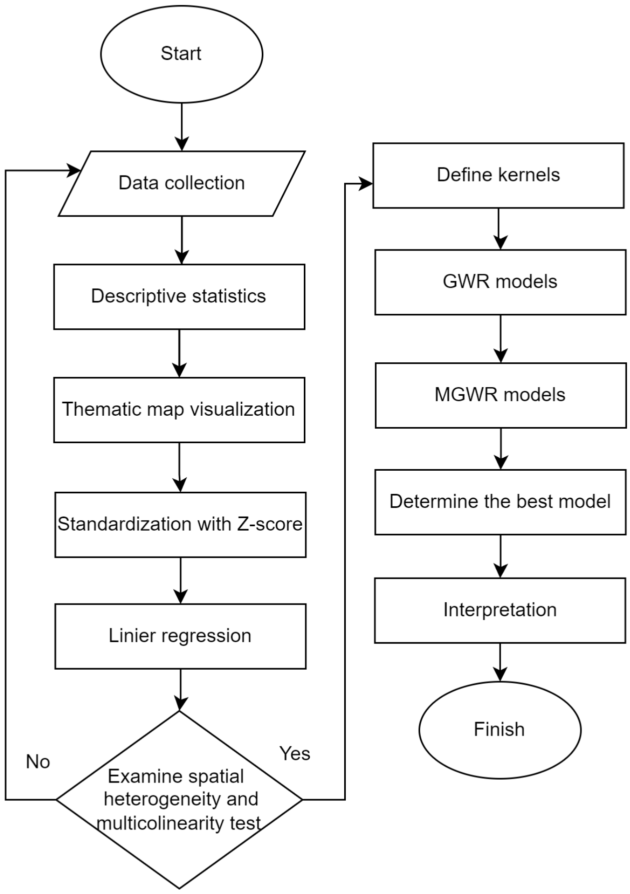

Fig. 1. Research Flow

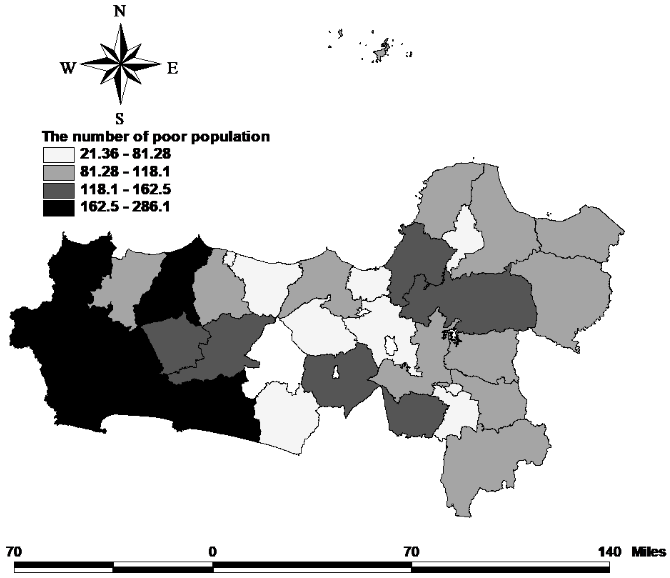

Fig. 2. Mapping of the number of poor populations in Central Java

TABLE IV
GLOBAL MODEL RESULT USING OLS REGRESSION

Parameter	Estimate	Std. Error	t-value	p-value
β_0	0.000	0.113	0.00	1.00
β_1	0.308	0.153	2.01	0.04
β_2	0.142	0.259	0.55	0.58
β_3	0.228	0.149	1.53	0.13
β_4	-0.669	0.239	-2.80	0.01

The large population contributes to poverty, as it results in an average of 2.86 percent and a maximum of 11.74 percent of the population living in poverty. The average years of schooling is 8.26, which is below the national target of 12 years of compulsory education

B. Overview of the Poor Population in Central Java in 2023 and its Influencing Factors

The first step in determining whether or not the spatial effect exists is through map visualization. We present a data distribution map showing the number of poor populations for each regency or city. The mapping result is shown in Fig. 2. The polygons on the map show the regencies or cities in Central Java, which have many regencies 25. The colours on the map show the number of poor populations in each regency or city with the rules; if the colour of the polygon is close to dark, then the regencies or cities have a high number of poor populations. Otherwise, if the colour of the polygon is close to light or white, then the regencies or cities have a low number of poor populations. Visually, it can be seen that the polygon colours are almost the same, indicating a spatial correlation between regencies or cities in Central Java.

C. OLS Regression Analysis

OLS modelling is performed before proceeding to GWR modelling, as shown in TABLE IV. Based on TABLE IV, the formula from multiple linear regression is as follows:

$$Y = 0 + 0.308X_1 + 0.142X_2 + 0.228X_3 - 0.669X_4$$

The parameter estimate that is significant in the regression is β_4. If the open unemployment rate (X_1) increases by 1%, the number of poor populations (Y) will decrease by 0.308. Then, if the life expectancy (X_2) increases by one year, the number of poor populations will increase by 0.142. Furthermore, if the percentage of the poor population (X_3) increases by 1%, the number of poor populations will increase by 0.228. For the average years of schooling (X_4), if this variable increases by one year, the number of poor populations will decrease by 0.669. Therefore, the average years of schooling must be improved to decrease the number of poor people in these regencies or cities.

The multiple linear regression model, which has an R^2 value of 0.62, accounts for a substantial amount of the variability in the number of poor populations. This underscores the importance of our study in understanding and addressing poverty. The variable with the most significant effect is the average years of schooling. In contrast, although not substantial, the other three variables are still included in the study to account for potential spatial heterogeneity effects, which will be further tested in the following hypothesis:
H_0: No spatial heterogeneity
H_1: Spatial heterogeneity

TABLE V
SPATIAL HETEROGENEITY TEST RESULTS

Test	Breusch-Pagan Test	p-value
Breusch-Pagan	9.89	0.04

Based on Table V, a p-value of 0.04 less than $\alpha = 0.05$ indicates that H_0 is rejected. This means there is a diversity of variance between observations or spatial heterogeneity. This issue can be addressed by employing local modelling and considering the spatial aspect, specifically the diversity between observations, allowing for the implementation of Geographically Weighted Regression (GWR) analysis. Our findings have significant implications for policymakers, researchers, and academics in social and economic development.

The next stage is to ensure that the four independent variables are not collinear using the variance inflation factor (VIF). VIF was initially performed to prevent potential multicollinearity among the four explanatory variables, as shown in TABLE VI.

TABLE VI
MULTICOLLINEARITY TEST RESULTS

Variable	VIF	Tolerance
X_1	1.83	0.55
X_2	5.25	0.19
X_3	1.75	0.57
X_4	4.47	0.22

The VIF values for all four variables are all less than 10, and the tolerance levels exceed 0.1, indicating that there is no collinearity among the independent variables. Therefore, the GWR model was utilized to examine the correlations between the number of poor populations and the independent variables.

D. Modelling with Geographically Weighted Regression (GWR)

Based on the testing of spatial effects assumptions, it is identified that the data contains spatial heterogeneity. Therefore, the next stage will involve modelling GWR. The next stage calculates the bandwidth with a fixed Gaussian kernel, which produces a value of 0.960. Since the kernel function is a fixed Gaussian kernel, the resulting bandwidth for each regency or city in Central Java will be identical. The GWR model estimation is conducted using a fixed Gaussian weighting function. The Weighted Least Square (WLS) method is essential in this process. The GWR model involves locally estimating parameters, where the parameter values differ for each location. TABLE VII summarises the parameter estimation results for the GWR model.

TABLE VII
SUMMARY OF GWR MODEL

Parameter	Min.	StDev	Mean	Median	Max.
β_0	-0.026	0.041	0.067	0.083	0.121
β_1	-0.020	0.145	0.284	0.323	0.477
β_2	-0.143	0.086	0.054	0.073	0.237
β_3	0.108	0.181	0.317	0.255	0.741
β_4	-0.778	0.142	-0.566	-0.614	-0.229

Based on TABLE VII, the values show the estimator's minimum and maximum values, which are the ranges for the estimated value of the variable; for example, in the open unemployment rate, the parameter estimate ranges from a minimum of -0.020 to a maximum of 0.477, indicating that its impact on the number of poor people varies between -0.02 and 0.477 In the GWR model, the parameter value is calculated at each observation point, resulting in distinct parameter values for every observation point. TABLE VIII shows an example of parameter estimation in a GWR model for the Banjarnegara regency.

TABLE VIII
PARAMETER ESTIMATION OF GWR MODEL OF BANJARNEGARA

Parameter	Estimate	Std. Error	t-value	p-value
β_0	0.072	0.119	0.606	0.547
β_1	0.473	0.160	2.947	0.005
β_2	0.198	0.266	0.745	0.462
β_3	0.141	0.140	0.999	0.322
β_4	-0.755	0.248	-3.039	0.004

The parameter estimation results in TABLE VIII indicate that two variables are significant in the models: the open unemployment rate and the average years of schooling. Overall, the estimated parameters generated with the GWR model show that the life expectancy variable has no significant effect throughout Central Java. The estimated model form of the GWR parameter with the fixed Gaussian weighting function for each region in Central Java is shown in TABLE IX.

Based on TABLE IX the GWR model estimation results for 35 regencies or cities in Central Java are presented, with the following GWR model obtained for the Banjarnegara regency as an example

$$Y = 0.072 + 0.473X_1 + 0.198X_2 + 0.141X_3 - 0.755X_4$$

Based on the obtained model, it can be concluded that a 1% increase in the open unemployment rate will lead to an increase of 0.473 in the number of poor populations. Similarly, if the life expectancy rises by one year, the number of poor populations will grow by 0.198. An increase of 1% in the percentage of the poor population will also raise the number of poor populations by 0.141. Conversely, for the average years of schooling, a one-year increase will reduce the number of poor populations by 0.755. Based on the parameters of the significant independent variables in each regency or city, the GWR modelling results with the fixed Gaussian weighting function form five groups, as shown in Fig. 3.

Based on Fig. 3, it can be seen that five groups are formed; the first group consists of 3 significant variables, namely the open unemployment rate, the percentage of the population, and the average years of schooling. The second group consists of the open unemployment rate and the average years of schooling. Group three includes the percentage of the population and average years of schooling. The fourth and fifth groups correspond to the percentage of the population and average years of schooling variables, respectively. In total, 26 regions indicate that the average years of schooling variable is significant, highlighting the need for the Central Java Provincial government to prioritize efforts to raise the average years of schooling. This result was obtained by Sudaryati and Ahmad, who stated that the average number of school years significantly affected poverty [21].

TABLE IX
GWR MODEL ESTIMATION

Regency or City	Model				
	Intercept	X_1	X_2	X_3	X_4
Banjarnegara	0.07	0.47	0.20	0.14	-0.76
Banyumas	0.08	0.29	0.06	0.28	-0.59
Batang	-0.02	-0.02	-0.14	+0.74	-0.23
Blora	0.10	0.36	0.08	0.21	-0.63
Boyolali	0.11	0.38	0.08	0.15	-0.65
Brebes	0.11	0.39	0.09	0.17	-0.66
Cilacap	0.07	0.28	0.08	0.25	-0.61
Demak	0.04	0.16	-0.02	0.47	-0.45
Grobogan	0.09	0.32	0.07	0.23	-0.61
Jepara	0.00	0.01	-0.14	0.71	-0.25
Karanganyar	0.12	0.43	0.07	0.11	-0.66
Kebumen	0.10	0.36	0.08	0.20	-0.64
Kendal	-0.01	0.08	-0.03	0.55	-0.40
Klaten	0.06	0.22	0.01	0.39	-0.50
Magelang City	0.02	0.10	-0.06	0.56	-0.37
Pekalongan City	0.05	0.48	0.24	0.16	-0.78
Salatiga City	0.09	0.41	0.14	0.22	-0.69
Semarang City	0.10	0.43	0.12	0.15	-0.69
Surakarta City	0.04	0.19	0.03	0.40	-0.51
Tegal City	-0.03	0.03	-0.05	0.61	-0.36
Kudus	0.08	0.43	0.17	0.20	-0.72
Magelang	0.11	0.41	0.09	0.13	-0.67
Pati	0.11	0.43	0.10	0.13	-0.68
Pekalongan	0.03	0.20	0.06	0.35	-0.55
Pemalang	0.11	0.41	0.09	0.14	-0.67
Purbalingga	0.09	0.33	0.08	0.26	-0.61
Purworejo	0.10	0.37	0.11	0.23	-0.65
Rembang	0.00	0.04	-0.11	0.66	-0.30
Semarang	0.09	0.39	0.14	0.26	-0.67
Sragen	0.09	0.32	0.07	0.22	-0.62
Sukoharjo	0.10	0.42	0.13	0.17	-0.69
Tegal	0.06	0.25	0.06	0.31	-0.57
Temanggung	0.08	0.29	0.05	0.31	-0.57
Wonogiri	0.05	0.16	-0.03	0.48	-0.43
Wonosobo	0.02	0.13	-0.01	0.49	-0.44

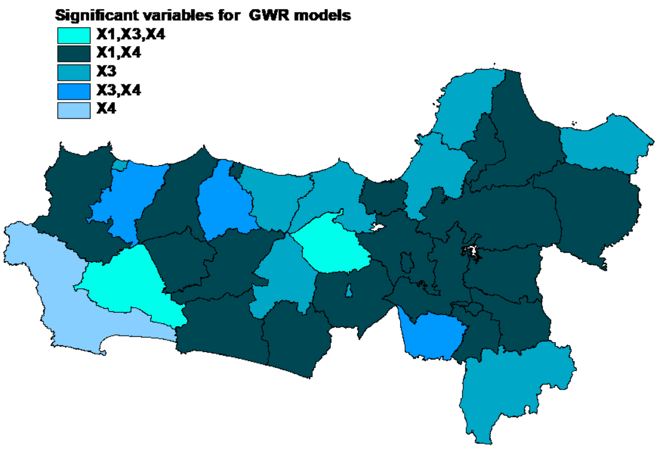

Fig. 3. GWR Significant Variables Distribution Map

To assess whether a significant difference exists between the OLS and GWR models, the method suggested by Brunsdon, Fotheringham, & Charlton (2002) was utilized. The hypothesis test applied is as follows:
H_0: There is no significant difference between the OLS and GWR model.
H_1: There is a significant difference between the OLS and GWR model.

TABLE X
GWR SUITABILITY TESTING

Test	F-test	p-value
BFC02	6.30	0.004

Based on TABLE X, the p-value 0.004 is less than α 0.05, indicating a significant difference between the OLS and the GWR model. The model evaluation results obtained using the GWR model are the R2 value of 72.9%, AIC 71.399, and MSE 0.271.

When testing the significance of the GWR model parameters, it was found that not all variables are significant at each observation location. This indicates that certain variables might not demonstrate a location effect. When a parameter lacks a location effect, it is considered a global coefficient, implying that it has the same estimated value at all observation locations. Therefore, a spatial variability test will be performed to identify any variable parameters without a location effect. This test will also distinguish between global and local coefficients for use in MGWR modelling with the following hypothesis.
H_0: $\beta_j(u_1,v_1) = \beta_j(u_2,v_2) = \ldots = \beta_j(u_i,v_i)$, where $j = 1,2,\ldots,p$ and $i = 1,2,\ldots,n$ (There is no significant difference in variable x_j from one location to another).
H_1: At least one $\beta_j(u_i,v_i) \neq \beta_j(u_{\neq i},v_{\neq i})$, where $j = 1,2,\ldots,p$ and $i = 1,2,\ldots,n$ (There is a significant difference in variable x_j from one location to another).

TABLE XI
SPATIAL VARIABILITY TEST

Parameter	p-value
β_0	0.173
β_1	0.049
β_2	0.165
β_3	0.091
β_4	0.097

Based on Table XI, the variable open unemployment rate has a p-value of 0.049, which is less than $\alpha = 5\%$. This indicates that there is a notable difference in the open unemployment rate from one location to another. Therefore, it can be concluded that the open unemployment rate follows a local model. In contrast, life expectancy, population percentage, and average years of schooling are considered global variables.

E. Modelling with Mixed Geographically Weighted Regression (MGWR)

Based on the significant variables in GWR output, we know global and local variables in the predictors affecting poor populations. Furthermore, the analysis can be continued by using MGWR. TABLE XII summarises the parameter estimation results for the MGWR model.

TABLE XII
SUMMARY OF MGWR MODEL

Parameter	Min.	St. Dev	Mean	Median	Max.
β_0	-0.264	0.176	0.127	0.198	0.319
β_1	-0.138	0.238	0.331	0.352	0.626
β_2	0.065	0.001	0.067	0.067	0.070
β_3	0.020	0.144	0.292	0.302	0.535
β_4	-0.510	0.007	-0.499	-0.500	-0.487

Based on TABLE XII, the values show the estimator's minimum and maximum values, which are the ranges for the estimated value of the variable. For example, the parameter estimate for the open unemployment rate has a minimum value of -0.138 and a maximum value of 0.319. Therefore, the impact of the open unemployment rate on the number of poor people varies from -0.138 to 0.319.

Subsequently, to assess whether the spatially varying relationships in the MGWR model offer a better fit compared to the global coefficients of multiple linear regression, the MGWR model fit test is conducted
H_0: $\beta_1 = \beta_2 = \cdots = \beta_n$, where $j = 1, 2, \ldots, p$ and $i = 1, 2, \ldots, n$ (There is no difference between multiple linear regression models and MGWR).
H_1: At least one $\beta_i \neq \beta_j$, where $j = 1, 2, \ldots, p$ and $i = 1, 2, \ldots, n$ (There is a difference between multiple linear regression models and MGWR).

TABLE XIII
MGWR MODEL FIT TEST RESULTS

Test Statistic	df_1	df_2	p-value
1.08	33.316	24.012	0.428

Based on TABLE XIII, the MGWR model fit test results show $F(1) = 1.08$ and $F_{(0.05;33.16;24.01)} = 1.921$. The p-value is 0.428, and with $\alpha = 0.05$, the decision is to fail to reject H_0.

Following the suitability test of the MGWR model, a simultaneous test will be conducted on the global parameters of the MGWR model. This simultaneous global parameter testing aims to assess whether the global variables simultaneously have a significant effect on the response variable.

H_0: There is no simultaneous effect of global variables on the response variable.
H_1: At least one global variable effect the response variable.

TABLE XIV
SIMULTANEOUS TEST OF GLOBAL PARAMETERS OF MGWR MODEL

F(2)	df_1	df_2	p-value
1.198	7.9	24.012	0.341

Based on TABLE XIV, the results of the simultaneous test of the global parameters of the MGWR model show that the F(2) value is 1.198 and the critical value $F_{(0.05;7.90;24.01)}$ is 2.36. The p-value is 0.341, which is greater than $\alpha = 0.05$, so the decision is to fail to reject H_0. Therefore, global variables do not have a simultaneous effect on the response variable.

Next, a simultaneous test will be conducted on the local parameters of the MGWR model. Local parameter testing is conducted to assess whether local variables have a significant simultaneous effect on the response variable.
H_0: $\beta_1(u_i, v_i) = \beta_2(u_i, v_i) = \ldots = \beta_q(u_i, v_i) = 0$ (There is no effect of local variables on the response variable)
H_1:$\beta_j(u_i, v_i) \neq 0$ (At least one local variable affects the response variable)

TABLE XV
SIMULTANEOUS TEST OF LOCAL PARAMETERS OF MGWR MODEL

F(3)	df_1	df_2	p-value
2.321	33.367	24.012	0.0175

Based on TABLE XV, the results from the simultaneous test of the MGWR model's local parameters indicate that the $F(3)$ value is 2.321, while the critical value $F_{(0.05;33.36;24.01)}$ is 0.54. The p-value is 0.0175, which is greater than $\alpha = 0.05$, leading to the decision to reject H_0. Thus, local variables have a simultaneous effect on the response variable.

To gain a deeper insight into the impact of individual global variables, a partial test is conducted. This test is useful in identifying which specific global variables significantly influence the number of poor people in Indonesia.
H_0: $\beta_j = 0$ (global variable x_j not significant)
H_1: At least one $\beta_j \neq 0$ (global variable x_j significant)

TABLE XVI
PARTIAL TEST OF GLOBAL PARAMETERS OF MGWR MODEL

Variable	t-test	df	p-value
Life Expectancy Rate (X_1)	0.110	3.612	0.000
Percentage of Population (X_2)	4.989	3.612	0.000

Based on the results in TABLE XVI of the simultaneous test of local parameters of the MGWR model obtained $|t_{test}|$ is 0.11 and $t_{(0.025;3.612)}$ is -2.898, the p-value is 0.00 and $\alpha = 0.05$ so that a decision can be made to reject H_0. This means that the Life Expectancy Rate and Population Percentage variables are significant to the MGWR model. Thus, the parameter estimation values for both variables are constant for regencies or cities in Central Java.

The next step involves conducting the partial test on the local parameters in the MGWR model.
H_0: $\beta_(u_i, v_i) = 0$ (Local variable x_j at location i is not significant)
H_1: At least one $\beta_j \neq 0$ (Local variable x_j at location i is significant)

Based on the results obtained in Fig. 4, it shows the significant variables in each regency or city in Central Java Province. Local variables are considered significant if they have a value of $|T_{test}| \geq T_{(0.025;3.612)}$ is -2.898. It can be observed that each regency or city in Central Java has different significant local variables. However, overall, regencies or cities in Central Java have the influence of local variables on their respective numbers of poor populations, with at least one local variable being significant.

The estimated model form of the MGWR parameter with the fixed Gaussian weighting function for each region in Central Java is shown in TABLE XVII.

TABLE XVII presents the estimation results for the GWR model applied to 35 regencies or cities in Central Java. For example, in the Banjarnegara regency, the resulting MGWR

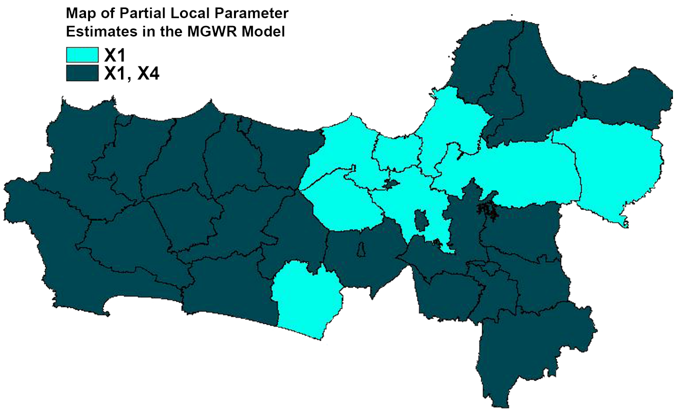

Fig. 4. Map of Partial Local Parameter Estimates in the MGWR Model

TABLE XVII
MGWR MODEL ESTIMATION BY REGENCY OR CITY

Regency or City	Model				
	Intercept	X_1	X_2	X_3	X_4
Banjarnegara	0.05	0.37	0.04	0.24	-0.48
Banyumas	0.28	0.30	0.04	0.34	-0.47
Batang	-0.24	-0.06	0.05	0.60	-0.45
Blora	0.31	0.51	0.04	0.24	-0.47
Boyolali	0.33	0.54	0.04	0.09	-0.47
Brebes	0.31	0.57	0.04	0.15	-0.47
Cilacap	0.23	0.15	0.04	0.28	-0.47
Demak	0.10	0.11	0.04	0.47	-0.46
Grobogan	0.31	0.32	0.04	0.25	-0.47
Jepara	-0.15	0.04	0.04	0.59	-0.46
Karanganyar	0.27	0.62	0.04	0.01	-0.48
Kebumen	0.32	0.52	0.04	0.21	-0.47
Kendal	-0.14	-0.07	0.04	0.51	-0.46
Klaten	0.20	0.20	0.04	0.45	-0.46
Magelang City	-0.02	0.07	0.04	0.51	-0.46
Pekalongan City	-0.06	0.28	0.04	0.48	-0.48
Salatiga City	0.14	0.56	0.04	0.40	-0.47
Semarang City	0.25	0.59	0.04	0.10	-0.47
Surakarta City	0.11	0.07	0.04	0.41	-0.46
Tegal City	-0.22	-0.16	0.04	0.55	-0.46
Kudus	0.08	0.49	0.04	0.43	-0.47
Magelang	0.30	0.60	0.04	0.06	-0.47
Pati	0.26	0.60	0.04	0.05	-0.48
Pekalongan	0.07	0.04	0.04	0.38	-0.46
Pemalang	0.30	0.60	0.04	0.08	-0.47
Purbalingga	0.28	0.50	0.04	0.36	-0.47
Purworejo	0.23	0.58	0.04	0.36	-0.47
Rembang	-0.13	0.01	0.04	0.56	-0.46
Semarang	0.11	0.57	0.04	0.52	-0.47
Sragen	0.31	0.33	0.04	0.24	-0.47
Sukoharjo	0.21	0.57	0.04	0.21	-0.47
Tegal	0.22	0.15	0.04	0.35	-0.46
Temanggung	0.28	0.36	0.04	0.40	-0.47
Wonogiri	0.13	0.17	0.04	0.50	-0.46
Wonosobo	-0.02	0.01	0.04	0.47	-0.46

model is as follows:

$$Y = 0.045 + 0.373X_1 + 0.04X_2 + 0.238X_3 - 0.478X_4$$

Based on the obtained model, an increase of 1% in the open unemployment rate is associated with a rise of 0.373 in the number of poor populations. A one-year increase in life expectancy results in an increase of 0.04 in the number of poor populations. Similarly, if the percentage of the poor population rises by 1%, the number of poor populations will increase by 0.238. In contrast, a one-year increase in the average years of schooling leads to a decrease of 0.478 in the number of poor populations.

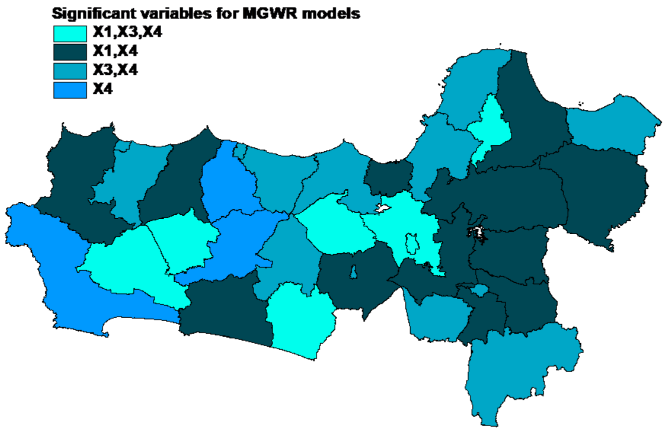

Fig. 5. MGWR Significant Variables Distribution Map

According to Fig. 5, four distinct groups have been identified. The first group includes three significant variables: the open unemployment rate, the percentage of the population, and the average years of schooling. The second group is composed of the open unemployment rate and the average years of schooling. The third group contains the percentage of the population along with the average years of schooling, while the fourth group solely consists of the average years of schooling variable. This grouping indicates that the average years of schooling is the global variable, highlighting its significance across regencies or cities in Central Java. Model evaluation results obtained from the MGWR model reveal an R^2 value of 82.3%, an AIC of 62.766, and an MSE of 0.177.

V. MODEL COMPARISON

Based on the analysis results obtained by comparing the GWR and MGWR models, the AIC, R^2, and MSE values are shown in TABLE XVIII.

TABLE XVIII
COMPARISON OF OLS, GWR, AND MGWR MODEL INDICATORS

Model	AIC	R^2	MSE
OLS	75.745	61.7%	0.383
GWR	71.399	72.9%	0.271
MGWR	62.766	82.3%	0.177

Based on TABLE XVIII, the MGWR model outperforms both OLS and GWR, as it has a higher goodness-of-fit R^2 and a lower AIC value. Additionally, MGWR achieves the lowest mean square error among the three models, further demonstrating its effectiveness. Consequently, the MGWR model is chosen to explain the relationship between the number of poor populations in Central Java.

VI. DISCUSSION

The distribution of R^2 values across regencies or cities in Central Java shows significant variation when using GWR and MGWR models, reflecting the different levels of accuracy in explaining the relationship between the variables investigated in each region shown in Fig. 5 and Fig. 6.

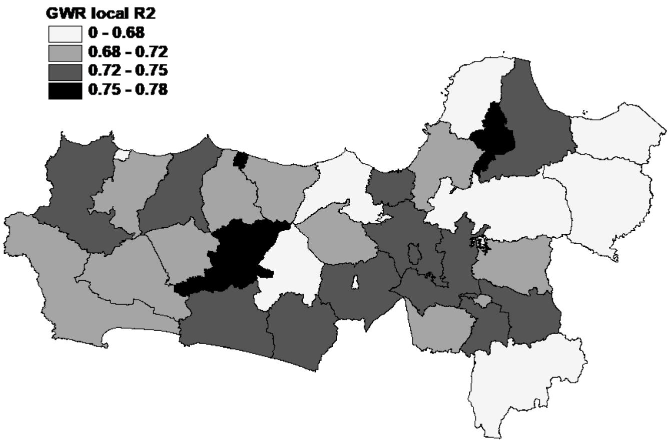

Fig. 6. Spatial distribution of local R^2 GWR

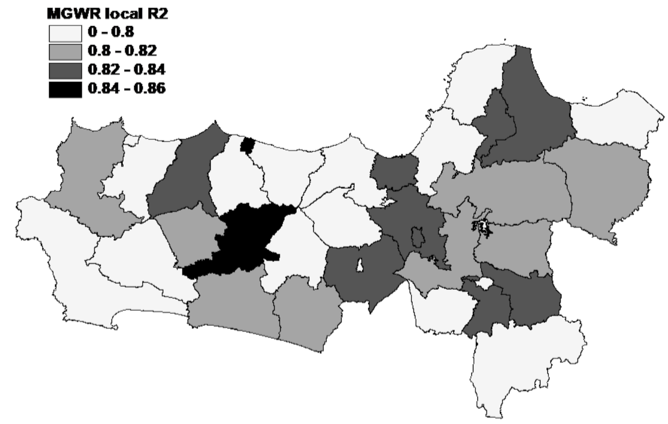

Fig. 7. Spatial distribution of local R^2 MGWR

Based on Fig. 6 and Fig. 7, the spatial heterogeneity in subnational fitting is demonstrated by the locally varying R^2 values for both the GWR and MGWR models. The Central Java region using the GWR model mostly has R^2 in the range of 68% to 75%, and only a few areas, such as Pekalongan City, Banjarnegara, and Pati, have a range of 75%-78%. Similarly, using the MGWR model, the Central Java region has more R^2 in the 80% to 84% range, and only a few areas, such as Pekalongan City, Banjarnegara, and Kudus, have a range of 84% to 86%. The local R^2 of the MGWR model demonstrates that it offers accurate predictions and better elucidates local relationships ($R^2 > 77\%$) in nearly all regencies or cities across Central Java. Overall, GWR and MGWR modeling produce similar accuracy levels, but MGWR modeling produces a greater value.

The performance of the local model is illustrated by plotting the observed values against the predicted values of the number of poor populations, as shown in Fig. 8 and Fig. 9.

Although the R^2 values of the GWR and MGWR models are not significantly different, Fig. 8 shows that the MGWR model provides slightly richer estimates for the number of poor populations compared to OLS and GWR. In this research, both GWR and MGWR models on the life expectancy variable were insignificant globally or locally.

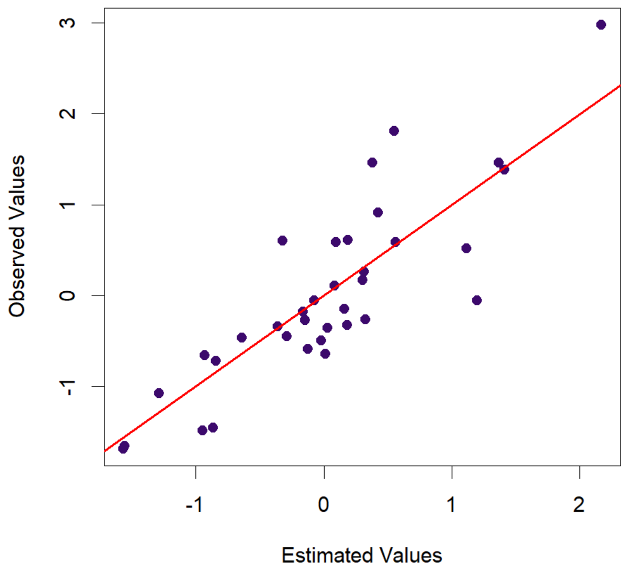

Fig. 8. Observed values versus estimated values of GWR models

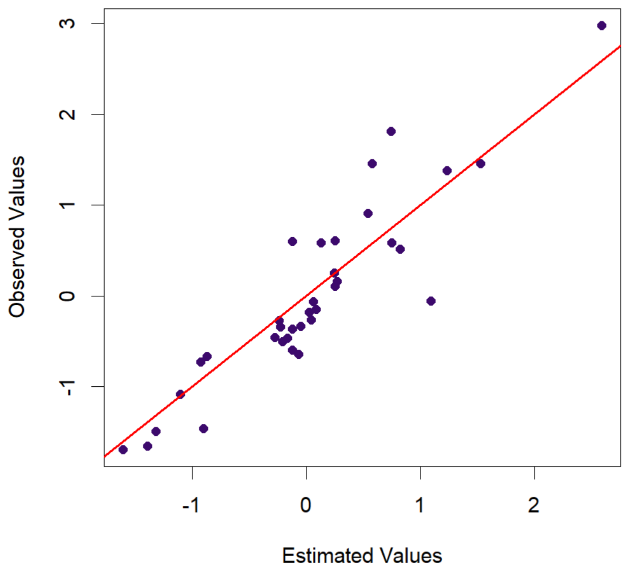

Fig. 9. Observed values versus estimated values of MGWR models

The results of the GWR and MGWR models indicate that the average years of education have a negative and significant impact on the number of poor populations. This means that the lower the average years of schooling taken by the community, the higher the number of poor populations. This is according to research conducted by Cahyo et al., which states that the relationship between the average years of schooling and poverty is expressed as an inversive relationship [22]. It means with higher levels of education, poverty will decrease.

Research conducted by Mardiyana also states that education negatively and significantly affects poverty [23]. Statistics Indonesia, National Socio-Economic Survey (Susenas) March 2023, the average years of schooling in Indonesia is 9.13 years, while in Central Java, it is only 8.01 years [24]. The average length of schooling in Indonesia is 9.13 years or equivalent to grade 9 junior high school. At the same time, in Central Java it is only 8.01 years or equivalent to grade 8 junior high school, of course this is still far from the mandatory education rate determined by the Indonesian government, which is 12 years of mandatory education [25].

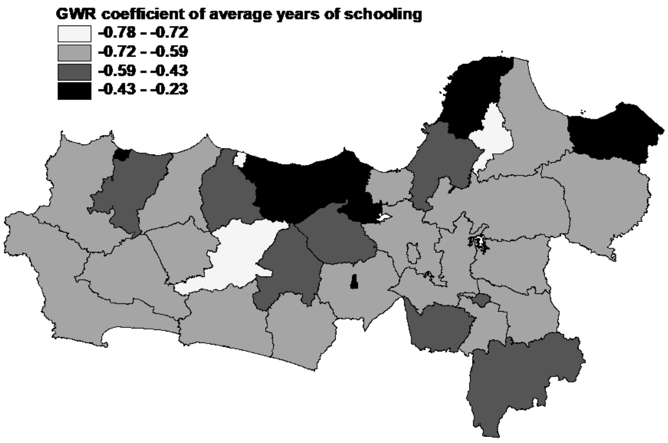

Fig. 10. GWR coefficient of average years of schooling

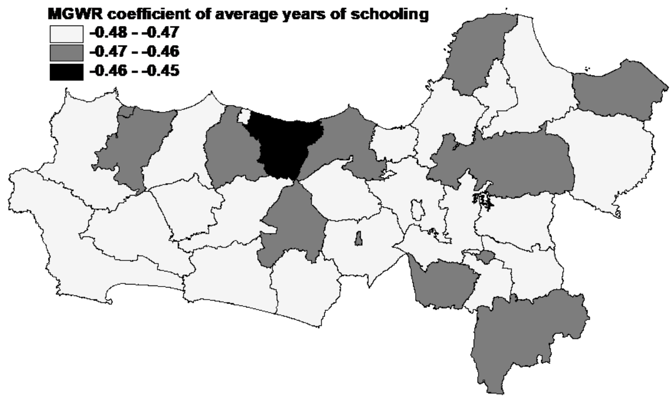

Fig. 11. MGWR coefficient of average years of schooling

Fig.10 and Fig.11 show that the GWR model produces a wider range from -0.78 to -0.23, indicating that the impact of average years of schooling on poverty varies significantly across different regions in Central Java. In some areas, increasing average years of schooling has a more significant effect (coefficient close to -0.78) on poverty reduction than in other regions (coefficient close to -0.23). However, using the MGWR model results in a narrower range from -0.48 to -0.45, indicating that the impact of average years of schooling on poverty is more equal across Central Java regions in the MGWR model. The negative relationship between average years of schooling and poverty can be understood through the statement that children from poor families tend to have lower academic achievement compared to children from more economically well-off families, so they have the potential not to complete their education within the ideal time frame [26].

Based on Fig. 12 and Fig. 13, it can be seen that using the GWR and MGWR models shows that in some regencies or cities, the open unemployment rate has a fragile negative relationship with the number of poor people, namely in the Batang region. Compared to the GWR model, the negative relationship between the open unemployment rate and poverty is more robust in some areas, especially in Tegal City, indicating that an increase in open unemployment significantly reduces the dependent variable in that region. This study shows that persistent open unemployment can lead to social instability and increased poverty. Overall, the MGWR model shows a broader variation in the effect of the open unemployment rate, both in the positive and negative directions, compared to the GWR model, which reflects a more controlled spatial variation and may be more accurate in explaining the local effect of the open unemployment rate on poverty in different regions.

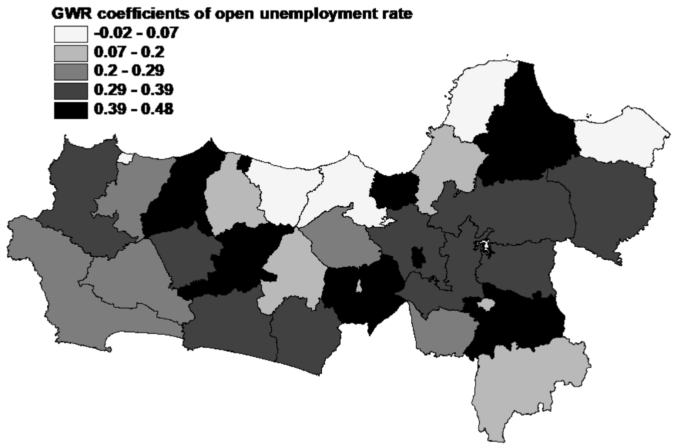

Fig. 12. GWR coefficient of open unemployment rate

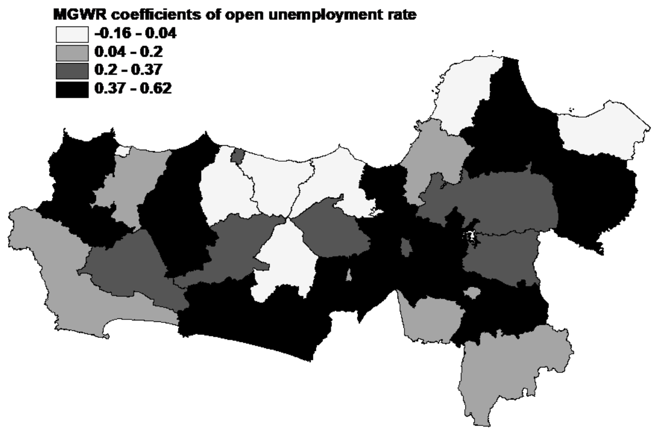

Fig. 13. MGWR coefficient of open unemployment rate

Based on Fig. 14 and Fig. 15, the MGWR model shows that the relationship between the percentage of poor population and the dependent variable is more moderate and less spatially variable than the GWR model. This can indicate that the MGWR model provides a more stable and controlled estimate of the impact of poverty in various regions. However, the impact remains significant and positive in all regions studied. This means that a higher percentage of the population in Central Java will result in an increase in poverty.

VII. Conclusion

From the research conducted, it is concluded that the modelling of the prediction of the number of poverty population on the dataset published by the CAS of the Central

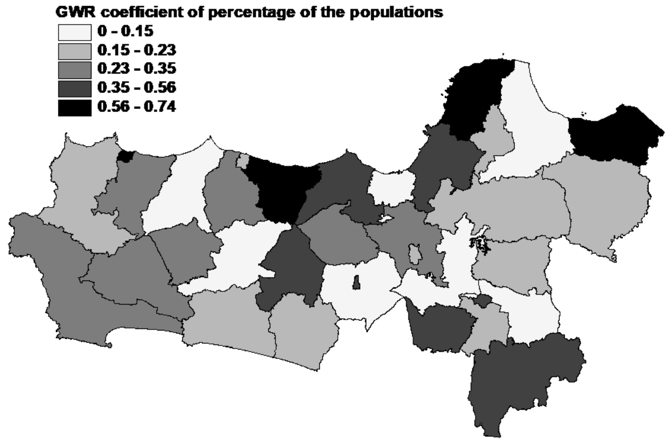

Fig. 14. GWR coefficient of percentage of the populations

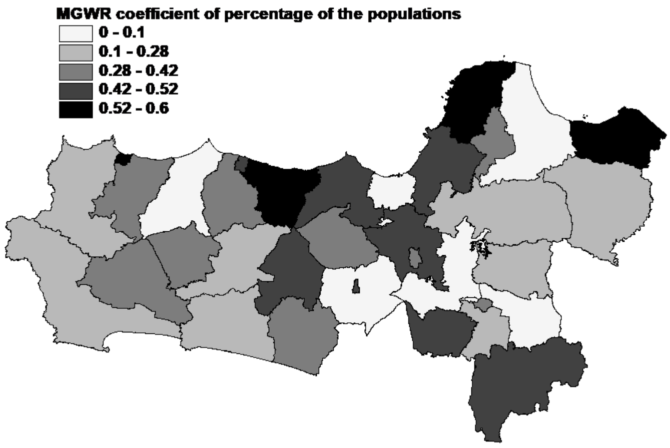

Fig. 15. MGWR coefficient of percentage of populations

Java region in 2023, using four variables, namely X_1 (Open Unemployment Rate), X_2 (Life Expectancy), X_3 (Population Percentage), and X_4 (Average Schooling Period), representing the survival, health, population, and education sectors respectively. Assumption test results show that the dataset indicates heteroscedasticity and should be approached using the spatial method. The best spatial regression model obtained is the one with the smallest error value and the largest R^2. In this study, the best model obtained is the Mixed Geographically Weighted Regression (MGWR) with AIC, R^2, and MSE values of 62.766, 82.3%, and 0.177, respectively. This condition implies that the response variable, the number of poverty populations in districts or cities in Central Java, can be explained by as much as 82.3% by the four predictor variables in the model formed. The best spatial model is expected to help the local government in regional poverty prediction with promisingly accurate results.

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