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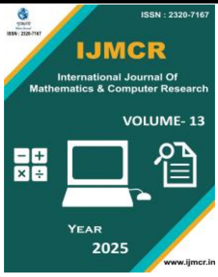

Spatial Analysis of Poverty in Central Java Indonesia Through Multiscale Geographically Weighted Regression

Dira Raina Agustina[1], Agus Rusgiyono[2], Prajna Pramita Izati[3]

[1,2,3] Department of Statistics, Universitas Diponegoro, Indonesia

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Corresponding Author:
Prajna Pramita Izati

ABSTRACT

Multiple linear regression is a statistical analysis method used to measure the influence of two or more independent variables on the dependent variable. Violation of the assumption of homoscedasticity in multiple linear regression analysis modeling can occur due to spatial heterogeneity. Therefore, it is necessary to analyze by providing spatial weights for each observation location. Multiscale Geographically Weighted Regression (MGWR) is a method developed to analyze spatial data with different scales of influence for each independent variable. This study aims to model the number of poor people in districts/cities in Central Java Province in 2023 using MGWR with the fixed gaussian kernel function. Average Wage of Laborers/Employees/Staff (X_1), Average Wage/Net Salary of Informal Workers (X_2), Number of TKI AKAN (X_3), Number of Unemployed Workers (X_4), APK SLTA (X_5), Number of people aged 15+ who have smoked in the past month (X_6), Percentage of Households Having Access to Clean Drinking Water Sources (X_7), and Percentage of Households Having Access to Proper Sanitation (X_8) each have an effect on the Number of Poor Population (Y) in at least one observation location. The MGWR model has an R^2 value of 0.8780482 and an $R^2_{adjusted}$ of 0.8200639.

KEYWORDS: MGWR; Fixed Gaussian Kernel; Number of Poor Population

I. INTRODUCTION

Poverty remains a major issue across many countries, including Indonesia. Addressing poverty is the first of the seventeen goals outlined in the Sustainable Development Goals (SDGs) framework. In addition, poverty alleviation is a key priority in Indonesia's national development agenda, as stated in the 2020–2024 National Medium-Term Development Plan (RPJMN) [1]. The Indonesian Central Bureau of Statistics (BPS) defines poverty based on the ability to meet basic needs, classifying individuals as poor if their average per capita expenditure falls below the poverty line. Data from BPS reveal that Java Island—particularly Central Java Province—has one of the highest poverty rates in the country. In fact, Central Java ranks second in Java Island for the highest percentage of people living in poverty, with a poverty rate of 10.77 percent. One approach to addressing this issue is by identifying the key factors that potentially contribute to poverty. This condition is multidimensional and exhibits spatial patterns, influenced by a complex interplay of social, environmental, and economic factors [2].

Regression analysis is a commonly used tool to examine the relationship between variables and to estimate the value of a dependent variable based on known independent variables. Parameter estimation in linear regression models typically relies on the Ordinary Least Squares (OLS) method, which requires several statistical assumptions to be met. However, in social data such as poverty data, spatial heterogeneity often exists, leading to violations of key assumptions—particularly the assumption of homoscedasticity—thereby reducing the reliability of the model due to unaccounted spatial effects.

To address this issue and capture spatial variation in poverty-related factors, spatial regression models are commonly employed, with Geographically Weighted Regression (GWR) being one of the most widely applied methods. GWR allows for spatially varying relationships between variables by estimating local regression coefficients for each location. These coefficients are calculated using data from neighboring areas, weighted by their distance from the focal location [3].

In the GWR model, the weighting process is influenced by the bandwidth parameter. A larger bandwidth tends to produce parameter estimates that resemble global trends, whereas a smaller bandwidth yields more localized parameter estimates [3]. However, a notable limitation of GWR is its use of a single bandwidth across all variables and locations, which may not adequately represent local spatial relationships occurring at different spatial scales. Some covariates may have highly localized effects, while others may influence broader regions. Moreover, poverty-related variables cannot be effectively analyzed using a uniform modeling approach, as each region possesses unique characteristics that shape the direction and intensity of these relationships.

To address this limitation, the Multiscale Geographically Weighted Regression model has been proposed. Multiscale Geographically Weighted Regression enhances the traditional GWR framework by allowing each explanatory variable to operate at its own optimal spatial scale through variable-specific bandwidths. This capability enables more precise estimation of spatially varying relationships, particularly in datasets characterized by heterogeneous spatial processes [2]. A study by Siallagan and Pusponegoro [4] compared various spatial regression methods, including Geographically Weighted Regression (GWR), mixed GWR, and Multiscale Geographically Weighted Regression (MGWR), in analyzing poverty rates. The results indicated that MGWR outperformed the other models, making it the most effective method for capturing spatial heterogeneity in poverty data. Another study conducted by Priliyan and Mahdy [5] compared MGWR and GWR models in analyzing open unemployment rates, and found that the MGWR model performed better, as indicated by a higher adjusted R^2 and a lower AICc value.

Poverty is a multidimensional issue influenced by a variety of factors. Previous studies have identified several variables that significantly impact poverty, such as wages/salaries [6], the number of migrant workers [7], gross enrollment rates [8], the number of unemployed labor force members [9], the percentage of the population who smoke [10], and the proportion of households with access to clean drinking water and proper sanitation [11]. Based on this context, the present study aims to apply the Multiscale Geographically Weighted Regression method to model the number of people living in poverty, to examine the indicators influencing poverty levels, and to identify the spatial variation in the effects of independent variables on poverty across the 35 regencies and municipalities in Central Java.

II. THEORETICAL FRAMEWORK

A. Regression Analysis

The multiple linear regression model expresses a linear correlation between a dependent variable and two or more independent variables [12]. The general formulation of the multiple linear regression model with p independent variables and n observations, where $i = 1,2,\dots,n$ [13], can be written as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_p X_{pi} + \varepsilon_i.$$

Let Y_i denote the dependent variable at observation point i, X_{pi} the independent variable p at observation point i, β_0 the intercept, β_p the regression coefficient for independent variable p, and ε_i the error term or residual at observation point i. Parameter estimation in the multiple linear regression model can be performed using the Ordinary Least Squares (OLS) method, resulting in the following equation:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{Y}$$

where $\hat{\boldsymbol{\beta}}$ is the vector of least square estimators for $\hat{\beta}_0$, $\hat{\beta}_1, \dots,$ $\hat{\beta}_p$, $\mathbf{X}$ denotes the matrix of independent variables, dan $\mathbf{Y}$ is the vector of dependent variables [13].

B. Multiscale Geographically Weighted Regression

The multiple linear regression model becomes suboptimal when spatial heteroskedasticity is present, thus requiring modeling methods that account for spatial aspects. Multiscale Geographically Weighted Regression (MGWR) is a method for modeling spatial data that allows each independent variable to exert influence at different spatial scales. The general formulation of the MGWR model with p independent variables [2] can be written as follows:

$$Y_i = \beta_{bw_0}(u_i, v_i) + \beta_{bw_1}(u_i, v_i)X_{1i} + \dots + \beta_{bw_p}(u_i, v_i)X_{pi} + \varepsilon_i$$

where Y_i denotes the dependent variable at observation point i, bw_0 is the bandwidth for intercept, bw_p is the bandwidth for independent variable p, X_{pi} is the value of independent variable p at observation point i, $\beta_{bw_0}(u_i, v_i)$ represents the intercept at location (u_i, v_i), $\beta_{bw_p}(u_i, v_i)$ is the regression coefficient for independent variable p at location (u_i, v_i), and ε_i denotes the residual at observation point i.

C. Multiscale Geographically Weighted Regression Estimation

The parameter estimates in the MGWR model are obtained through a calibration process using a backfitting algorithm by representing Geographically Weighted Regression (GWR) as a Generalized Additive Model (GAM). The calibration process of the MGWR model begins with the initialization of an additive structure, which includes the smoothed functions of each independent variable $\hat{f}_k$, the residual matrix $\hat{\varepsilon}$, the hat matrix $\boldsymbol{S}$, and the variable-specific additive hat matrix $\boldsymbol{R}_k$ derived from GWR. In each MGWR iteration, the residuals $\hat{\varepsilon}$ are computed and added to the smoothing function, which is then regressed on $\boldsymbol{X}_k$ using GWR. Each GWR analysis conducted during the iteration yields a specific bandwidth bw_k. The residual matrix $\hat{\varepsilon}$ is defined as follows:

$$\hat{\boldsymbol{\varepsilon}} = \boldsymbol{Y} - \sum_{k=0}^{p} \hat{\boldsymbol{f}}_k$$

In the first iteration, a GWR analysis is conducted by regressing the sum of the residuals and the initial value of the first smoothing function $(\hat{\boldsymbol{f}}_0 + \hat{\boldsymbol{\varepsilon}})$ on the first covariate $(\boldsymbol{X}_0)$, resulting in the bandwidth bw_0 and $\boldsymbol{A}_0$ as the hat matrix from the GWR model $\{(\hat{\boldsymbol{f}}_0 + \hat{\boldsymbol{\varepsilon}}) \sim \boldsymbol{X}_0\}$. Then, in the backfitting algorithm procedure of the MGWR model, each fitted term is updated as follows:

$$\hat{\boldsymbol{f}}_k^* = \boldsymbol{A}_0(\hat{\boldsymbol{f}}_k + \hat{\boldsymbol{\varepsilon}})$$

$\hat{\boldsymbol{f}}_k$ denotes the additive component predicted from the previous iteration, while $\hat{\boldsymbol{f}}_k^*$ represents the updated additive component. $\boldsymbol{R}_k$ within the hat matrix $\boldsymbol{S}$ is replaced by $\boldsymbol{R}_k^*$ resulting in an updated hat matrix $\boldsymbol{S}^*$, which is defined as follows:

$$\boldsymbol{S}^* = \boldsymbol{S} - \boldsymbol{R}_k + \boldsymbol{R}_k^*$$

and

$$\boldsymbol{R}_k^* = \boldsymbol{A}_k\boldsymbol{R}_k + \boldsymbol{A}_k - \boldsymbol{A}_k\boldsymbol{S}.$$

The iterative process is completed when all updated additive components $\hat{\boldsymbol{f}}_k^*$ have converged. The output of the backfitting algorithm includes the optimal bandwidth for the k-th variable $(bw_{i,k})$, the AICc value, and the estimated parameter for the k-th variable $(\hat{\beta}_{ki})$, defined as follows:

$$\hat{\boldsymbol{f}}_k^* = \begin{bmatrix} x_{k1}\hat{\beta}_{k1} \\ x_{k2}\hat{\beta}_{k2} \\ \vdots \\ x_{kn}\hat{\beta}_{kn} \end{bmatrix}; k \quad = 0,1,2,\ldots,p$$

and

$$\hat{\beta}_{ki} = \boldsymbol{e}_k(\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{Y}$$

$\boldsymbol{e}_k$ is the k-th row vector of the identity matrix of size $(p+1)\times(p+1)$, and $\boldsymbol{W}_i$ is the weighting matrix for observation point i. In the final iteration, all resulting $\boldsymbol{R}_k^*$ matrices can be used to determine the effective number of parameters (ENP) for each covariate, denoted as ENP_k, which is obtained from the following equation:

$$ENP_k = trace(\boldsymbol{R}_k^*)$$

The sum of all ENP_k is equal to the ENP for the entire model. ENP serves as the total degrees of freedom of the MGWR model, indicating the estimated number of independent parameters in the MGWR model calculation.

The MGWR modeling assigns weights w_{ij} to each observation point, which are written in a weight matrix $(\boldsymbol{W}_i)$. The spatial weighting is given using a fixed Gaussian kernel weight function [14], expressed as follows:

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

where d_{ij} is the Euclidean distance and $bw_{i,k}$ is the optimal bandwidth, which adapts from one location to another. The selection of the optimal bandwidth is performed by minimizing the corrected Akaike Information Criterion (AICc):

$$AICc(bw) = 2n.ln(\hat{\sigma}) + n.ln(2\pi) + n\left\{\frac{n + tr(\boldsymbol{S})}{n - 2 - tr(\boldsymbol{S})}\right\}$$

where $\hat{\sigma}$ is the estimated standard deviation of the error term, $tr(\boldsymbol{S})$ is the trace of the hat matrix, and nnn is the number of observations.

III. RESEARCH METHODS

The data used in this study were obtained from the official website of the Central Java Province Statistics Agency (Badan Pusat Statistik) at https://jateng.bps.go.id/id and from a geospatial data platform at https://geosai.my.id/. The variables utilized in the analysis include: the number of people living in poverty, average wages/salaries of workers and employees, average income of informal workers, number of Indonesian migrant workers (TKI AKAN), number of unemployed individuals in the labor force, gross enrollment rate at the senior high school level, number of individuals aged 15 and above who smoked in the past month, percentage of households with access to clean drinking water, and percentage of households with access to adequate sanitation. The study employs data from the year 2023, with the unit of analysis consisting of 35 regencies and municipalities within Central Java Province. The analysis was carried out through the following steps:

1. Data collection. Collecting data from official Badan Pusat Statistik sources and geospatial platforms.
2. Descriptive analysis. Performing descriptive statistics to understand data distribution.
3. Multiple linear regression. Constructing a baseline global multiple linear regression model.
4. Heteroscedasticity test. Testing for heteroscedasticity to determine model suitability.
5. MGWR modeling. Applying MGWR to capture multiscale spatial heterogeneity.
6. Model interpretation. Interpreting the local parameter estimates from the MGWR model.
7. Visualization. Mapping estimated coefficients to reveal spatial variation.

IV. RESULT AND DISCUSSION

Based on the descriptive-statistical analysis, the number of poor residents (Y) in the regencies and cities of Central Java in 2023 averages 108.33 thousand people. This figure indicates that, overall, poverty remains substantial in the province. The relatively large standard deviations observed for each variable suggest considerable dispersion, implying that the data for both the dependent and independent variables are unevenly distributed across districts and municipalities. A detailed summary—including minimum, maximum, mean, and standard-deviation values for all variables—is presented in Table I.

The multiple linear regression analysis produced the following model:

$$\begin{aligned}\hat{Y} = 0{,}93514 &- 0{,}000025594X_1 - 0{,}000019377X_2 \\ &- 0{,}00035296X_3 + 0{,}00025039X_4 \\ &- 0{,}54086X_5 + 0{,}00044568X_6 \\ &- 0{,}39597X_7 - 1{,}184X_8\end{aligned}$$

Table I. Descriptive Statistical Analysis Of Research Variables

Variable	Min.	Max.	Avg.	Std. Dev.
Y	7.45	286.14	108.328	60.5939
X_1	1810299	3505157	2287612	329486.8
X_2	1069756	2558972	1610742	292391
X_3	40	11344	1685.914	2328.374
X_4	3632	93374	30864.57	22073.75
X_5	61.98	112.3	89.50571	12.54243
X_6	22895	485130	239436.9	111355.3
X_7	66.77	98.36	82.28057	8.457656
X_8	46.09	98.15	85.30771	12.06212

Heteroskedasticity was tested on the multiple linear regression model using the Breusch Pagan Godfrey procedure. The test produced a statistic of $\chi2 = 19.923$ with an associated $p_{value} = 0.01063$. At the 5 % significance level ($\alpha = 0.05$) and with $n = 35$ observations ($k = 8$ regressors), the critical value is $\chi^2_{k;\alpha} = 15.51$. Because $\chi^2_{BPG} = 19.923 > 15.51$ and $p_{value} = 0.01063 < 0.05$, the null hypothesis of homoskedastic errors is rejected. Thus, the residuals exhibit heteroskedasticity.

Heteroskedasticity may stem from spatial heterogeneity; therefore, the data were re-modelled with Multiscale Geographically Weighted Regression (MGWR) to obtain a better fit. Using a back-fitting calibration procedure, optimal bandwidths were selected by minimising the corrected Akaike information criterion (AICc). The resulting optimal bandwidths and corresponding parameter estimates for each independent variable are summarised in Table II.

The varying bandwidth values indicate that the independent variables have an influence at different spatial scales. Referring to Table 2, it is found that the parameters X_1, X_2, X_3, X_4, and X_5 have an influence at a broader spatial scale, while variable X_7 influences at a medium spatial scale, and variables X_6 and X_8 have an influence at a smaller spatial scale. The bandwidth together with Euclidean distance is used to determine the magnitude of the spatial weights. Since each variable has its own bandwidth value, the assignment of weights to the observation points is also adjusted for each variable. For example, the weight matrix for variable X_1 can be reviewed in Table III.

Table II. Optimum Bandwidth Values For Research Variables

Variable	Bandwidth
X_1	2.6639
X_2	2.6670
X_3	2.6682
X_4	2.6682
X_5	2.6658
X_6	1.0115
X_7	1.2604
X_8	1.0549

Table III. Weight Matrix For Variable X_1

Location	Banjarnegara	Banyumas	...	Wonosobo
Banjarnegara	1	0.9831	...	0.9953
Banyumas	0.9831	1	...	0.9629
⋮	⋮	⋮	⋱	⋮
Wonosobo	0.9953	0.9629	...	1

Meanwhile, the estimated parameter values for each point can be reviewed in Table IV.

Table IV. Estimated Parameter Values For Research Variables In The MGWR Model

Location	Intercept	β_1	β_2	⋯	β_8
Banjarnegara	15.37	-2.95×10^{-5}	-1.55×10^{-5}	...	-0.98
Banyumas	31.80	-2.99×10^{-5}	-1.55×10^{-5}	...	-0.89
Batang	5.13	-2.92×10^{-5}	-1.54×10^{-5}	⋯	-1.02
Blora	51.45	-2.80×10^{-5}	-1.54×10^{-5}	...	-1.38
Boyolali	19.79	-2.87×10^{-5}	-1.55×10^{-5}	...	-1.19
Brebes	37.05	-3.00×10^{-5}	-1.53×10^{-5}	...	-0.85
⋮	⋮	⋮	⋮	⋮	⋮
Wonosobo	7.34	-2.93×10^{-5}	-1.55×10^{-5}	...	-1.03

The varying estimated parameter values for each observation point indicate that the significance of the independent variables is not uniform across all points but instead varies individually for each observation point. For example, the estimated parameter value β_8 in Batang Regency is -1.02, while in Brebes Regency, it is -0.85. This value indicates that variable X_8 has a more dominant influence on the number of poor people in Batang Regency compared to the number of poor people in Brebes Regency.

After obtaining the MGWR model for each location, a normality assumption test was performed using the Kolmogorov-Smirnov test. It was found that the residuals are normally distributed because the calculated D value (D_{value})

is less than the table value (D_{table}) ($KS_{(n,1-\alpha)}$), specifically 0.090644 < 0.224, and the p_{value} is greater than α, i.e., 0.9111 > 0.05. A local non-multicollinearity assumption test was also conducted to examine the presence or absence of correlations between the independent variables in the model by checking the VIF values. Based on the analysis results, the VIF values for each independent variable in all MGWR models did not exceed 10, indicating that local multicollinearity is not present. The VIF values for the significant independent variables at each location can be reviewed in Table V.

Table V. VIF Values For Independent Variables In The MGWR Model

Loc.	VIF Value							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Banjar.	2.933	3.268	2.208	6.105	2.215	5.878	2.601	2.007
Banyu.	2.967	3.311	2.257	6.288	2.274	6.046	2.827	2.136
Batang	2.916	3.229	2.178	5.995	2.180	5.783	2.435	1.930
Blora	2.816	3.119	2.066	5.560	2.024	5.392	2.377	1.658
Boyolali	2.866	3.198	2.127	5.801	2.110	5.601	2.464	1.797
Brebes	2.981	3.302	2.267	6.327	2.288	6.093	2.816	2.146
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Wonos.	2.916	3.254	2.188	6.030	2.190	5.808	2.561	1.957

The MGWR analysis process is continued with a local hypothesis test to determine whether the independent variables significantly affect the dependent variable. The results of the local hypothesis test vary for each observation point, leading to the identification of 10 groups of locations based on the significant independent variables, which can be reviewed in Table VI.

Table VI. Group Of Regencies/Cities In Central Java Province

Group	Sig. Var.	Regency
1	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8$	Batang
2	$X_1, X_2, X_4, X_5, X_6, X_7, X_8$	Klaten, Pati
3	$X_1, X_2, X_5, X_6, X_7, X_8$	Banjarnegara, Blora, Boyolali, Demak, Grobogan, Jepara, Karanganyar, Kendal, Kota Surakarta, Kudus, Pekalongan, Pemalang, Purworejo, Rembang, Semarang, Sragen, Sukoharjo, Tegal, Temanggung, Wonogiri
4	X_1, X_2, X_5, X_6, X_8	Banyumas, Brebes, Cilacap
5	X_1, X_2, X_5, X_7, X_8	Kota Magelang, Kota Pekalongan, Kota Salatiga
6	X_1, X_2, X_5, X_8	Kota Tegal
7	$X_1, X_3, X_5, X_6, X_7, X_8$	Wonosobo
8	X_1, X_4, X_5, X_6, X_8	Purbalingga
9	X_1, X_5, X_6, X_7, X_8	Kota Semarang, Magelang
10	X_1, X_5, X_6, X_8	Kebumen

After obtaining the MGWR model for each location, a local non-multicollinearity assumption test was performed. For example, the MGWR model for Brebes Regency is as follows.

$$\begin{aligned}\hat{Y}_{Brebes} = {} & 37{,}0531 - 2{,}9972 \times 10^{-5}\, X_{1,6} \\ & - 1{,}5306 \times 10^{-5}\, X_{2,6} \\ & - 7{,}7077 \times 10^{-4}\, X_{3,6} \\ & + 1{,}0287 \times 10^{-4}\, X_{4,6} - 0{,}4993\, X_{5,6} \\ & + 5{,}0699 \times 10^{-4}\, X_{6,6} - 0{,}1212\, X_{7,6} \\ & - 0{,}8516\, X_{8,6}\end{aligned}$$

Through the results of the local hypothesis test, it was found that variables X_1, X_2, X_5, X_6, and X_8 significantly influence the number of poor people in Brebes Regency, while variables X_3, X_4, and X_7 do not have a significant effect. Referring to equation above, it is known that the intercept value in the MGWR model for Brebes Regency is 37.0531, meaning that when the independent variables are at zero, the number of poor people in Brebes Regency is 37.0531 thousand people. The value of β_1, which is -2.9972×10^{-5}, indicates that for every increase of 1 rupiah in the average wage of workers/employees, the number of poor people in Brebes Regency decreases by 0.029972 people. Thus, an average wage increase of 33.3645 rupiah is required to reduce the number of poor people by 1 person. The value of β_2, which is -1.5306×10^{-5}, indicates that for every increase of 1 rupiah in the average wage/salary of informal workers, the number of poor people in Brebes Regency decreases by 0.015306 people. Therefore, an increase in the average wage/salary of informal workers by 65.3339 rupiah is needed to reduce the number of poor people by 1 person. The value of β_5, which is -0.4993, reflects that for every 1% increase in the high school (SLTA) enrollment rate, the number of poor people in Brebes Regency decreases by 0.4993 thousand people. Thus, a 2.0028% increase in the high school enrollment rate is needed to reduce the number of poor people by 1 thousand. The value of β_6, which is 5.0699×10^{-4}, indicates that for every increase of 1 person in the population aged 15+ who smoked in the last month, the number of poor people in Brebes Regency increases by 0.50699 people. Therefore, the number of poor people will increase by 1 thousand if the number of smokers aged 15+ in the last month increases by 1,972.43 people or approximately 1,973 people. The value of β_8, which is -0.8516, indicates that for every 1% increase in the percentage of households with access to proper sanitation, the number of poor people in Brebes Regency decreases by 0.8516 thousand people. Therefore, a 1.1743% increase in the percentage of households with access to proper sanitation will reduce the number of poor people in Brebes Regency by 1 thousand.

Overall, the MGWR model that has been formed for all observation points has an R² value of 0.8780482, which indicates that 87.80482% of the variation in the number of poor people in the regencies/cities of Central Java can be explained by the covariates in the model. An adjusted R² value of 0.8200639 was also obtained. There is no significant difference between the adjusted R² and the R² values, indicating that the covariates in the model are indeed relevant and contribute significantly to the model. The high R² and adjusted R² values suggest that the MGWR model obtained in this study is very good.

The estimated parameter values for each MGWR model were then visualized with the aim of identifying the distribution and variation of the intercept values as well as the magnitude of the influence of the independent variables on the dependent variable in each regency and city in Central Java. For example, the mapping of the intercept values and $\hat{\beta}_1$ can be reviewed in Fig. 2 and Fig.3.

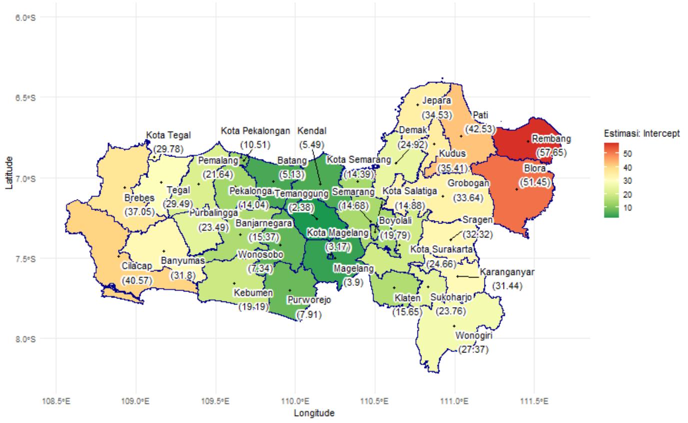

Figure 1. Mapping of Intercept Values in the MGWR Model

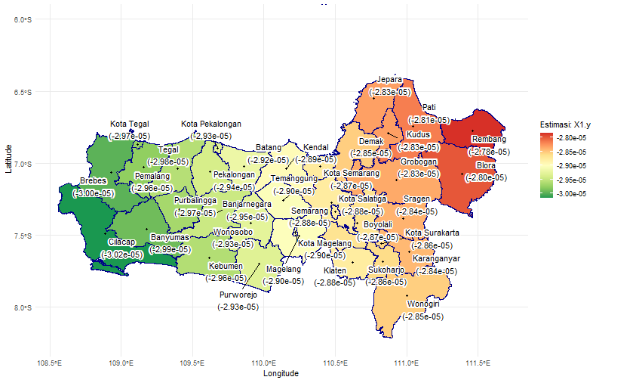

Figure 2. Mapping of Estimated Parameter Values for X_1 ($\hat{\beta}_1$) in the MGWR Model

Figure 2 shows the visualization of the intercept values from all the obtained MGWR models. This visualization was conducted to identify the distribution and variation of the intercept values in the regencies/cities of Central Java Province. The red color on the map indicates observation points with higher intercept values, the yellow color represents observation points with intercept values near the average value, and the green color shows observation points with lower intercept values. The varying intercept values and the similar color patterns of neighboring areas suggest that, without considering the significance of the covariates in the model, the baseline poverty levels in the regencies/cities of Central Java are not uniform. Each regency/city has specific conditions and characteristics that influence poverty, and neighboring locations tend to share similar characteristics related to poverty. The estimated parameter values of $\hat{\beta}_p$ were also visualized to identify the distribution and variation in the degree of influence of the independent variables on the dependent variable in the regencies/cities of Central Java.

Figure 3 shows the variation in the values of $\hat{\beta}_1$, with red indicating locations with smaller estimated parameter values, yellow representing locations with moderate estimated parameter values, and green for locations with larger estimated parameter values. This variation suggests that the influence of the variable X_1 (Average Wage of Workers/Employees) on the Number of Poor People (Y) is not global, but rather varies according to the characteristics of each observation point. Neighboring observation points tend to have the same color, indicating that the variable X_1 (Average Wage of Workers/Employees) influences the Number of Poor People (Y) in neighboring areas in a similar manner.

V. CONSLUSION

The MGWR modeling with a fixed Gaussian kernel function was chosen as a solution to handle heteroscedasticity that may arise due to spatial heterogeneity. In the modeling of the number of poor people in the regencies/cities of Central Java, 35 MGWR models were obtained corresponding to the number of regencies and cities in Central Java, with an overall

R^2 value of 0.8780482 and an adjusted R^2 value of 0.8200639, indicating that the MGWR model obtained in this study is very good. The factors significantly influencing the number of poor people vary for each observation point, resulting in 10 groups of regencies/cities in Central Java based on the significant independent variables in those areas. Each dependent variable in this study has a significant effect on the number of poor people in at least one region. Variables X_1, X_2, X_3, X_5, X_7 , and X_8 have a negative effect on Y, while variables X_4 and X_6 have a positive effect. Each independent variable affects the dependent variable at different spatial scales, and its influence varies according to the characteristics of each region.

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