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WASTE GENERATION MODELING BASED ON SOCIOECONOMIC AND SOCIODEMOGRAPHIC FACTORS IN WEST JAVA USING GEOGRAPHICALLY WEIGHTED REGRESSION

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Abstract: Waste has become a national concern, reflecting the increasing consumption patterns within society. The rise in consumption contributes to the growing volume and diversity of waste generated. West Java Province is one of the regions with the highest total waste generation in Indonesia. Several factors, particularly those related to socioeconomic and sociogeographic conditions, are believed to influence the annual increase in waste generation across the region. Therefore, this study aims to model the socioeconomic and sociogeographic factors influencing waste generation in West Java Province by incorporating spatial aspects using the Geographically Weighted Regression (GWR) method. Based on the analysis, the GWR model was applied using an adaptive bisquare kernel function, achieving a model fit of 96.65%. The factors found to have a significant influence on waste generation in West Java Province include life expectancy of schooling (HLS), the percentage of the population living in poverty, and the Gross Regional Domestic Product (GRDP) at constant prices.

1. INTRODUCTION

Waste-related issues have become a significant concern that both the government and society must address. Increasing consumption patterns in the community contribute to the growth of waste generation, consisting of various types. This problem is also aligned with the Sustainable Development Goals (SDGs), specifically Goal 12, which focuses on responsible consumption and production. In Indonesia, only about 39%–54% of waste is managed correctly, resulting in approximately 30–40 million tons of waste, including 3–4 million tons of plastic waste, polluting the environment each year [1] . Additionally, data from the National Waste Management Information System (SIPSN) indicate that in 2023, the total amount of waste generated in Indonesia was 42,858,021.33 tons. West Java Province is one of the regions with the highest total waste generation in the country. It was recorded that the total waste generation in West Java Province in 2023 was 7,575,071.20 tons, showing a significant increase compared to the total waste generation in 2022, which was only 5,427,324.84 tons [2]. In addition to the increase between 2022 and 2023, the total waste generation in West Java has also shown a consistent upward trend over the past five years.

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The annual increase in waste generated in West Java Province, particularly the approximately 39.57% rise in 2023 compared to 2022, is likely influenced by several factors. According to Prajati & Pesurnay [3], waste generation is closely linked to socioeconomic aspects such as regional economic capacity reflected in Gross Regional Domestic Product (GRDP) because higher economic activity and household purchasing power generally drive greater consumption and, consequently, larger volumes of waste. Sociodemographic factors also play a critical role, as population characteristics such as density, education level, and poverty status shape household behavior, resource use, and disposal patterns. Prajati and Pesurnay [4] further identified population density as a determinant of waste generation in nine provincial capitals on Sumatra Island, reinforcing the importance of demographic pressures in urban and semi-urban areas. In addition to these factors, variations in geographical, environmental, social, and economic conditions across districts and municipalities in West Java Province contribute to spatial disparities in waste generation, thus necessitating an analytical approach that incorporates both socioeconomic and sociodemographic dimensions.

In this study, a model will be developed to examine the factors influencing waste generation in West Java Province in 2023. The study also considers spatial point aspects, as each district or city may have different levels of waste generation, particularly in urban areas, which tend to produce more waste than rural areas. This condition may lead to spatial heterogeneity. One statistical method that can address spatial heterogeneity is Geographically Weighted Regression (GWR). In this modelling, parameter estimates will be obtained for each district or city regarding waste generation. Several recent studies have provided insights relevant to this research. Previous work applied spatial regression models such as SAR, SLX, and SDM in West Java and found that literacy levels, the number of MSMEs, traditional markets, and recreational or tourist sites significantly affect total waste generation [5]. Another study examined illegal waste dumping and demonstrated that elevation and population density are major determinants, while GWR outperformed ordinary least squares in capturing spatial variation [6]. However, these studies have not specifically integrated socioeconomic and sociodemographic factors within a GWR framework to model formal waste generation at the district/city level in West Java. Most existing research focuses on limited determinants or different types of waste-related problems, leaving a gap in comprehensive spatial modeling that simultaneously considers regional economic capacity, demographic characteristics, and geographic variation. Addressing this gap, the present study develops a GWR-based model that incorporates socioeconomic and sociodemographic factors to produce a more spatially nuanced and context-specific understanding of waste generation in West Java Province. The findings are expected to provide valuable insights for policy-making efforts to reduce waste in the years to come.

2. LITERATURE REVIEW

2.1. Multiple Linear Regression

This analysis is used to determine whether there is a significant influence of two or more predictor variables on the response variable [7]. The multiple linear regression model is shown in Equation (1).

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + \varepsilon; k = 1, 2, \dots, 4 \tag{1}$$

With,

β_0 = Estimated intercept

β_k = Estimated parameter for predictor variable X_k with $k = 1, 2, \dots, 4$

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ε = Error term

The method used to estimate the parameters of the multiple linear regression model is the Ordinary Least Squares (OLS) method, as presented in Equation (2).

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X})^{-1}(\boldsymbol{X}^{\boldsymbol{T}}\vec{\boldsymbol{y}}) \quad (2)$$

A simultaneous test is used to assess whether all predictor variables together have a significant influence on the response variable [8]. The hypotheses are formulated as follows:

H_0 : $\beta_1 = \beta_2 = \cdots = \beta_4 = 0$
H_1 : At least one $\beta_k \neq 0$, for k = 1, 2, …, 4

At a given significance level α, H_0 is rejected if $F_{calculated} > F_{(\alpha;p;n-p-1)}$ or P-*value* < α, which indicates that at least one predictor variable significantly affects the response variable. The simultaneous test statistics are shown in Equation (3):

$$F_{calculated} = \frac{MSreg}{MSerror} \quad (3)$$

A partial test is used to assess the effect of each individual predictor variable on the response variable [8]. The hypotheses are stated as follows:

H_0 : $\beta_k = 0$, for k =1, 2, …, 4
H_1 : $\beta_k \neq 0$, for k =1, 2, …, 4

At a given significance level α, H_0 is rejected if $|t| > t_{\left(\frac{\alpha}{2};n-p\right)}$ or P-*value* < α, which means that the k-th predictor variable significantly affects the response variable. The partial test statistic is shown in Equation (4):

$$t = \frac{\widehat{\beta}_k}{se(\widehat{\beta}_k)} \quad (4)$$

The classical assumptions in multiple linear regression modelling state that the residuals must satisfy the conditions of being multicollinearity, independent, identically distributed, and normally distributed. Multicollinearity occurs when there is a linear relationship among predictor variables in a multiple linear regression model, which can be detected using the Variance Inflation Factor (VIF) [9]. Identical residuals mean that the residuals have a homogeneous variance-covariance matrix, which can be tested using the Glejser test. Independent residuals indicate the absence of autocorrelation among residuals, and this assumption can be examined using the Durbin-Watson test. Meanwhile, the assumption of normality requires that residuals follow a normal distribution, which can be tested using the Kolmogorov-Smirnov test [10].

2.2. Spatial Heterogeneity Test

Spatial heterogeneity testing is required to identify the presence of spatial variability in the observed data [11]. The spatial heterogeneity test is conducted using the Breusch-Pagan statistical test. The Breusch-Pagan test for spatial heterogeneity is formulated as follows:

H_0 : $\sigma_1{}^2 = \sigma_2{}^2 = \cdots = \sigma_{23}{}^2 = \sigma^2$
H_1 : At least one $\sigma_i{}^2 \neq \sigma^2$ for i = 1, 2, ..., 23

At a given significance level α, H_0 is rejected if $BP > \chi^2{}_{(\alpha;p)}$ or P-Value < α, which means that spatial heterogeneity effects are present, the case can be addressed using a point-

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based approach and further proceeded with the Geographically Weighted Regression model. The Breusch-Pagan test statistic is presented in Equation (5).

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

2.3. Geographically Weighted Regression

The Geographically Weighted Regression (GWR) model is a regression model specifically designed to analyse data with a continuous response variable while considering spatial aspects [11]. The general form of the GWR model is shown in Equation (6).

$$Y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{23} \beta_k(u_i, v_i)\, X_{ik} + \varepsilon_i;\ i = 1, \dots, 23 \text{ dan } k = 1, \dots, 4 \tag{6}$$

With,

$\beta_k(u_i, v_i)$: The regression parameter for the *k*-th variable at the *i*-th observation point with coordinates

The parameter estimation used in the GWR model is the Weighted Least Squares (WLS) method, which assigns different weights to each observed location. The parameter estimation for each observation location is given in Equation (7).

$$\widehat{\boldsymbol{\beta}}(\boldsymbol{u_i}, \boldsymbol{v_i}) = (\boldsymbol{X^T W}(\boldsymbol{u_i}, \boldsymbol{v_i})\boldsymbol{X})^{-1}\boldsymbol{X^T W}(\boldsymbol{u_i}, \boldsymbol{v_i})\boldsymbol{Y} \tag{7}$$

Bandwidth is the radius of the estimation area centered at the i-th observation point. The bandwidth value is determined using the Cross Validation procedure as shown in Equation (8).

$$CV(h) = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(h)]^2 \tag{8}$$

There are two types of kernel functions: fixed and adaptive. The fixed kernel function has the same bandwidth value for all observation location [12]. Meanwhile, the adaptive kernel function has varying bandwidth values at each observation location, with the weighting function defined as follows:

Fixed Gaussian
$$w_j(u_i, v_i) = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right)$$

Fixed Bisquare
$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i}\right)^2\right]^2, & \text{for } d_{ij} < h_i \\ 0, & \text{for others} \end{cases}$$

Fixed Tricube
$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h}\right)^3\right]^3, & \text{for } d_{ij} < h \\ 0, & \text{for others} \end{cases}$$

Adaptive Gaussian
$$w_j(u_i, v_i) = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_i}\right)^2\right)$$

Adaptive Bisquare
$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i}\right)^2\right]^2, & \text{for } d_{ij} < h_i \\ 0, & \text{for others} \end{cases}$$

Adaptive Tricube
$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i}\right)^3\right]^3, & \text{for } d_{ij} < h_i \\ 0, & \text{for others} \end{cases}$$

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d_{ij} represents the distance between the point at location i and location j, which is calculated using the Euclidean distance formula as described in Equation (9).

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \quad (9)$$

Model adequacy testing for GWR is conducted using the F-test by Brunsdon, Fotheringham, and Charlton [13].

H_0 : $\beta_k(u_i, v_i) = \beta_k$, for i = 1, 2, …, 23 and k = 1, 2, ..., 4
H_1 : At least one $\beta_k(u_i, v_i) \neq \beta_k$, i = 1, 2, …, 23 and k = 1, 2, ..., 4

At a given significance level α, H_0 is rejected if $F > F_{(\alpha; df_1, df_2)}$ or P-*value* < α, which means that there is a significant difference between the OLS and GWR models. The test statistic is given in Equation (10).

$$F = \frac{\frac{(SSE(H_0) - SSE(H_1))}{v}}{\frac{SSE(H_1)}{\delta_1}} \quad (10)$$

In addition, the significance of the parameters in each model for every region is tested using a partial t-test with the following hypotheses:

H_0 : $\beta_k(u_i, v_i) = 0$, for i = 1, 2, …, 23 and k = 1, 2, ..., 4
H_1 : $\beta_k(u_i, v_i) \neq 0$, for i = 1, 2, …, 23 and k = 1, 2, ..., 4

At a given significance level α, H_0 is rejected if $|t| > t_{(\alpha/2; df_2)}$ or P-*value* < α, which means that $\beta_j(u_i, v_i)$ is significant to the response variable. The test statistics are given in Equation (11).

$$t = \frac{\hat{\beta}_k(u_i, v_i)}{\hat{\sigma}\sqrt{c_{kk}}} \quad (11)$$

The methods used in selecting the best model include Akaike's Information Criterion (AIC) and R^2, with the criteria explained in Equation 12 and 13.

$$AIC = 2n \log_{\varepsilon}(\hat{\sigma}) + n \log_{\varepsilon}(2\pi) + n + tr(\boldsymbol{S}) \quad (12)$$

$$R = \frac{\sum_{i=1}^{n} w_{ij}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} w_{ij}(y_i - \bar{y})^2} \quad (13)$$

3. METHODOLOGY

3.1. Data Sources and Research Variables

The data used in this study are secondary data obtained from the official website of the Central Statistics Agency (BPS) of West Java Province and waste generation data retrieved from the official website of the National Waste Management Information System (SIPSN). The unit of observation in this study is the regencies and cities in West Java Province for the year 2023. The research variables consist of four predictor variables, categorized into socioeconomic and sociodemographic aspects. The sociodemographic variables include population density (X_1) and life expectancy of schooling (X_2). In contrast, the socioeconomic variables include the number of people living in poverty (X_3) and the Gross Regional Domestic Product (GRDP) at constant prices (X_4).

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3.2. Analysis Procedure

The analytical steps carried out in this study to achieve the research objectives are described as follows:

1. Analyzing the characteristics of waste generation and socioeconomic and sociodemographic factors by regency/city in West Java Province.
2. Performing multiple linear regression modelling of waste generation based on socioeconomic and sociodemographic factors across regencies/cities in West Java Province.
3. Testing the spatial aspects of the waste generation data based on socioeconomic and sociodemographic factors across regencies/cities in West Java Province using the Breusch–Pagan (BP) test.
4. Developing a Geographically Weighted Regression (GWR) model for waste generation data based on socioeconomic and sociodemographic factors across regencies/cities in West Java Province.
5. Determining the best regression model by comparing the AIC and R^2 values of the multiple linear regression and GWR models.
6. Concluding and providing recommendations.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistic

The characteristics of the data used to analyze the waste generation model are presented through descriptive statistics, including the maximum value, minimum value, mean, and standard deviation.

Table 1. Descriptive Statistics

Variable	Minimum	Maximum	Mean	Standard Deviation
Amount of Waste Generation (Y)	31624	1026931	349438	255740
Population Density (X_1)	383	14776	4338	4751
Life Expectancy of Schooling (X_2)	11.910	14.290	12.994	0.776
Number of People Living in Poverty (X_3)	11.7	453.8	145.1	105.5
Gross Regional Domestic Product at Constant Prices (X4)	5245	393823	103843	113648

Based on Table 1, the average amount of waste generated in East Java in 2023 was 349438 tons, with a standard deviation of 255740 tons, indicating considerable variation between districts/cities, with the lowest amount being 31624 tons and the highest reaching 1,026,931 tons. The population density variable had an average of 4338 people per km²/km² with a standard deviation of 4751, reflecting a wide variation, as some areas had very low densities of 383 people/km². In comparison, other areas had very high densities of 14776 people/km². The average length of schooling was relatively uniform at 12.994 years, with a standard deviation of 0.776, ranging from a minimum of 11.91 years to a maximum of 14.29 years. The number of poor people shows a significant disparity, with an average of 145.1 thousand people and a standard deviation of 105.5 thousand people, ranging from 11,7 thousand to 453.8 thousand people. Meanwhile, the Gross Regional Domestic Product (GRDP) at constant prices was recorded at an average of 103.843 billion rupiah with a standard deviation of 113,648 billion rupiah, reflecting the high level of economic disparity between regions, from the lowest GRDP of 5.245 billion rupiah to the highest of 393.823 billion rupiah.

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4.2. Modeling Waste Generation in West Java Using Multiple Linear Regression

The multiple linear regression was developed through several stages, including multicollinearity, parameter estimation, simultaneous and partial significance test of parameters. The results of the multicollinearity test using VIF values are presented in Table 2.

Table 2. Multicollinearity Test Results

Variable	VIF
Population Density (X_1)	2.33
Life Expectancy of Schooling (X_2)	2.46
Number of People Living in Poverty (X_3)	2.23
GRDP at Constant Prices (X_4)	1.63

As shown in Table 2, all predictor variables have VIF values less than 10. Therefore, it can be concluded that there is no multicollinearity among the predictor variables.

The results of the parameter estimation for the multiple linear regression model regarding the influence of sociodemographic and socioeconomic factors on waste generation in West Java Province are as follows:

$$\hat{Y} = -812481 + 9.69X_1 + 58276X_2 + 1832X_3 + 0.933X_4$$

After estimating the parameters, a simultaneous significance test was conducted on all predictor variables. Based on the analysis, the F value is 47.991, which is greater than the critical value of $F_{(0.05;4;18)}$ of 2.928 and supported by a p-value of 0.000, which is less than the significance level of 0.05. Therefore, the null hypothesis is rejected, indicating that at least one predictor variable has a significant effect on the waste generation variable.

Following the simultaneous significance test, a partial significance test was conducted on each predictor variable. With a significance level of α is 0.05, the null hypothesis is rejected if $|t| > t_{(0.05;18)}$ or if the p-value is less than 0.05. Based on the analysis, the t-test results are presented in Table 3.

Table 3. Partial Significance Test

Parameters	|t|	$t_{0.05;18}$	P-Value
X_1	1.709	2.101	0.105
X_2	1.636		0.119
X_3	7.330		0.000
X_4	4.698		0.000

Based on Table 3, it can be concluded that the variables number of people living in poverty (X_3) and GRDP (X_4) have a significant effect on waste generation. The assumptions of identical, independent, and normally distributed residuals need to be tested in multiple linear regression analysis. Based on the results, the regression model was found to satisfy these assumptions.

4.3. Spatial Heterogeneity Test

Spatial heterogeneity was tested using the Breusch-Pagan (BP) test to determine whether there is variation in attribute values across regions [14]. Based on the analysis, the BP value was 10.125, which is greater than the critical value $\chi^2_{(0.05;4)}$ is 9.488 and supported by a p-value of 0.038, which is less than the significance level of 0.05. Therefore, the null hypothesis is rejected, indicating the presence of spatial heterogeneity, and therefore, analysis can be carried out using Geographically Weighted Regression (GWR).

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4.4. Modelling Waste Generation in West Java Using Geographically Weighted Regression

In GWR analysis, the optimal weighting is determined using the kernel function that performs best. The comparison of R^2 and AIC values for each kernel function is presented in Table 4.

Table 4. Comparison of Kernel Functions

Parameter	Gaussian		Bisquare		Tricube	
	Fix	Adaptive	Fix	Adaptive	Fix	Adaptive
R^2	0.951	0.956	0.942	0.968*	0.942	0.961
AIC	574.926	573.099	578.253	567.689*	578.389	571.050

Based on the highest goodness-of-fit (R^2) value of 0.968 and the lowest AIC value of 567.689, the best kernel function used in the GWR analysis is the Adaptive Bisquare function. The parameter estimation results of the Geographically Weighted Regression (GWR) model for waste generation in West Java Province are presented in Table 5.

Table 5. Parameter Estimation of the GWR Model

No	Regency/City	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
1	Bogor Regency	-1935698.726	-0.336	150071.965	1929.882	0.826
2	Cianjur Regency	-1659426.541	0.830	126750.430	1948.540	0.846
3	Bandung Regency	-569450.773	3.491	39075.277	1716.106	1.062
⋮	⋮	⋮	⋮	⋮	⋮	⋮
22	Tasikmalaya City	-112030.381	1.408	7770.360	1359.746	1.177
23	Banjar City	-112163.861	1.564	7802.735	1379.824	1.157

The significance testing of GWR consists of both simultaneous and partial tests. The simultaneous significance testing of the GWR model for waste generation in West Java, based on sociodemographic and socioeconomic factors. Based on the analysis results, the F value is 2.659, which is lower than the critical value of $F_{(0.05;18;11.684)}$ is 2.671 and this result is supported by a P-Value of 0.046, which is less than the significance level of 0,05. Therefore, the null hypothesis is rejected, indicating a significant difference between the OLS and GWR models.

After rejecting H_0 in the simultaneous significance test, a partial test was conducted on the GWR model. Based on the analysis, the critical value $t_{(\frac{0.05}{2};11.684)} = 2.201$. The partial test results showed that the variables of expected years of schooling, the number of people living in poverty, and GRDP at constant prices had a significant effect on waste generation in each district/city in West Java Province. Therefore, a new multiple linear regression model is constructed, excluding the population density variable (X_1), as follows:

$$\hat{Y} = -1224631 + 93653X_2 + 1729X_3 + 1.023X_4$$

Subsequently, a simultaneous significance test was conducted on the updated model without the population density variable. Based on the analysis results, the F value is 2.972, which is lower than the critical value of $F_{(0.05;19;13.211)}$ is 2.471, and this result is supported by a P-Value of 0.024, which is less than the significance level of 0.05. Therefore, the null hypothesis is rejected, indicating a significant difference between the OLS and GWR models.

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Then, the analysis proceeded with the partial significance test. At a significance level of 0,05, the null hypothesis is rejected if $|t| > t_{(0.05;13.211)}$ or P-Value < 0.05. The results of the GWR partial test are presented in Table 6.

Table 6. Partial Significance Test of the GWR Model

No.	Regency/City	t(X_2)	t(X_3)	t(X_4)	t(0.05;13.211)
1.	Bogor Regency	**5.703**	**9.123**	**5.486**	2.160
2.	Cianjur Regency	**5.038**	**9.290**	**5.769**	2.160
3.	Bandung Regency	1.503	**5.308**	**6.725**	2.160
4.	Garut Regency	0.394	**5.194**	**6.323**	2.160
5.	Tasikmalaya Regency	0.295	**5.277**	**6.180**	2.160
6.	Ciamis Regency	0.335	**5.414**	**6.345**	2.160
7.	Kuningan Regency	0.473	**5.613**	**6.554**	2.160
8.	Cirebon Regency	0.604	**5.630**	**6.632**	2.160
9.	Sumedang Regency	0.976	**5.305**	**7.039**	2.160
10.	Indramayu Regency	1.820	**5.793**	**7.223**	2.160
11.	Karawang Regency	**5.686**	**9.276**	**5.459**	2.160
12.	Bekasi Regency	**5.689**	**9.220**	**5.460**	2.160
13.	Bandung Barat Regency	2.542	**6.784**	**6.360**	2.160
14.	Pangandaran Regency	0.228	**5.153**	**5.975**	2.160
15.	Bogor City	**5.626**	**9.137**	**5.509**	2.160
16.	Sukabumi City	**5.172**	**9.221**	**5.740**	2.160
17.	Bandung City	0.964	**3.831**	**6.281**	2.160
18.	Cirebon City	0.617	**5.615**	**6.632**	2.160
19.	Bekasi City	**5.836**	**9.082**	**5.394**	2.160
20.	Depok City	**5.761**	**9.090**	**5.442**	2.160
21.	Cimahi City	1.564	**4.955**	**6.320**	2.160
22.	Tasikmalaya City	0.329	**5.376**	**6.297**	2.160
23.	Banjar City	0.331	**5.420**	**6.359**	2.160

Note: Bold values indicate statistical significance

Table 6 presents the parameters that are significant in each regency or city in West Java. Furthermore, the significant variables are grouped by regency or city in West Java, as presented in Table 7.

Table 7. Grouping of Significant Variables in Each Regency/City

No	Regency/City	Variables	No	Regency/City	Variables
1.	Bogor Regency	X_2, X_3, X_4	13.	Bandung Barat Regency	X_3, X_4
2.	Cianjur Regency	X_2, X_3, X_4	14.	Pangandaran Regency	X_3, X_4
3.	Bandung Regency	X_3, X_4	15.	Bogor City	X_2, X_3, X_4
4.	Garut Regency	X_3, X_4	16.	Sukabumi City	X_2, X_3, X_4
5.	Tasikmalaya Regency	X_3, X_4	17.	Bandung City	X_3, X_4
6.	Ciamis Regency	X_3, X_4	18.	Cirebon City	X_3, X_4
7.	Kuningan Regency	X_3, X_4	19.	Bekasi City	X_2, X_3, X_4
8.	Cirebon Regency	X_3, X_4	20.	Depok City	X_2, X_3, X_4
9.	Sumedang Regency	X_3, X_4	21.	Cimahi City	X_3, X_4
10.	Indramayu Regency	X_3, X_4	22.	Tasikmalaya City	X_3, X_4
11.	Karawang Regency	X_2, X_3, X_4	23.	Banjar City	X_3, X_4
12.	Bekasi Regency	X_2, X_3, X_4			

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The significant variables were grouped by regency/city in West Java, as presented in Table 7. Regencies/cities grouped based on similarities in variables that are significant for waste generation are explained in Table 8.

Table 8. Grouping of Regencies/Cities Based on Significant Variables

Group	Regency/City	Variable
1	Indramayu Regency, Cirebon Regency, Kuningan Regency, Ciamis Regency, Pangandaran Regency, Tasikmalaya Regency, Garut Regency, Bandung Regency, West Bandung Regency, Sumedang Regency, Cirebon City, Banjar City, Tasikmalaya City, Bandung City	X_3, X_4
2	Cianjur Regency, Bogor Regency, Bekasi Regency, Karawang Regency, Cimahi City, Sukabumi City, Bogor City, Depok City, Bekasi City,	X_2, X_3, X_4

Furthermore, the results of mapping regencies/cities in West Java province based on significant variables for waste generation are shown in Figure 1.

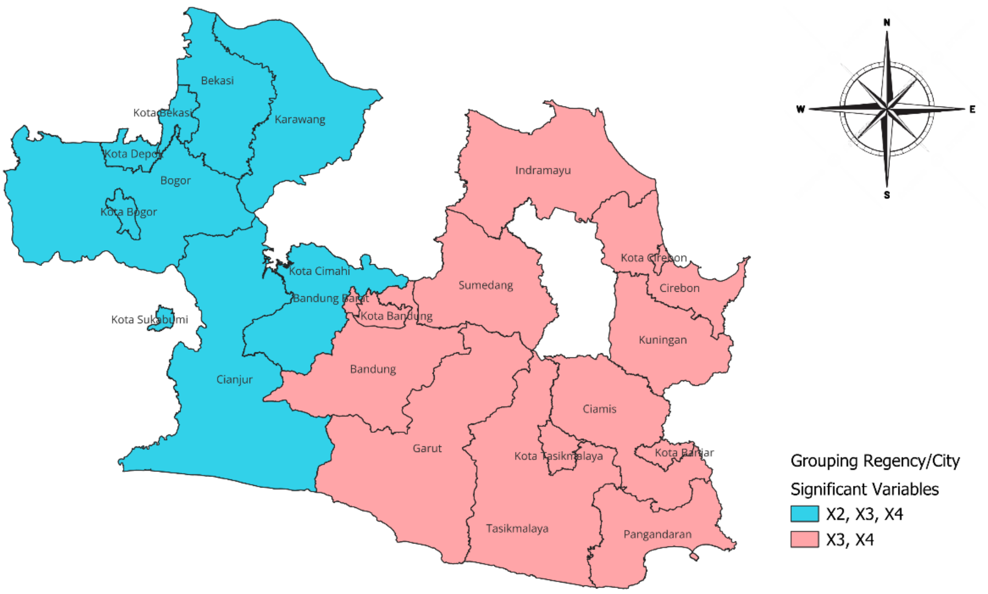

Fig 1. Map of Significant Variable Groupings

This map illustrates the grouping of regions based on the significant predictors identified in the GWR model, showing how socioeconomic and sociodemographic influences vary geographically. The western region of the province mostly shows significant variables in all three variables, namely X_2, X_3, and X_4, with 14 regencies/cities. In comparison, the central to eastern region shows significant variables in two variables, namely X_3 and X_4, with 9 regencies/cities. This spatial visualization shows the existence of spatial heterogeneity in West Java Province.

Subsequently, the GWR model for waste generation in each regency/city in West Java was developed, as shown in Table 9.

Table 9. GWR Model for Each Regency/City

No	Regency/City	Model
1.	Bogor Regency	$\hat{Y}$ = - 1916423.555 + $\mathbf{148410.204X_2}$ + $\mathbf{1932.276X_3}$ + $\mathbf{0.826X_4}$
2.	Cianjur Regency	$\hat{Y}$ = -1707174.472 + $\mathbf{130861.587X_2}$ + $\mathbf{1941.341X_3}$ + $\mathbf{0.847X_4}$
3.	Bandung Regency	$\hat{Y}$ = -704234.286 + $51406.533X_2$ + $\mathbf{1639.567X_3}$ + $\mathbf{1.101X_4}$
4.	Garut Regency	$\hat{Y}$ = -152904.586 + $11046.557X_2$ + $\mathbf{1324.692X_3}$ + $\mathbf{1.234X_4}$
5.	Tasikmalaya Regency	$\hat{Y}$ = -114742.991 + $8431.144X_2$ + $\mathbf{1315.247X_3}$ + $\mathbf{1.231X_4}$

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No	Regency/City	Model
6.	Ciamis Regency	$\hat{Y}$ = -129334.637 + 9533.046X_2 + **1341.551X_3** + **1.211X_4**
7.	Kuningan Regency	$\hat{Y}$ = -179902.719 + 13202.541X_2 + **1394.310X_3** + **1.178X_4**
8.	Cirebon Regency	$\hat{Y}$ = -229720.224 + 16814.425X_2 + **1437.139X_3** + **1.153X_4**
9.	Sumedang Regency	$\hat{Y}$ = -394560.860 + 28345.803X_2 + **1492.773X_3** + **1.162X_4**
10.	Indramayu Regency	$\hat{Y}$ = -690830.432 + 50689.689X_2 + **1696.491X_3** + **1.048X_4**
11.	Karawang Regency	$\hat{Y}$ = -1911065.186 + **147745.361X_2** + **1958.520X_3** + **0.824X_4**
12.	Bekasi Regency	$\hat{Y}$ = -1907217.954 + **147581.787X_2** + **1946.923X_3** + **0.823X_4**
13.	Bandung Barat Regency	$\hat{Y}$ = -1095337.760 + 80890.183X_2 + **1842.796X_3** + **0.994X_4**
14.	Pangandaran Regency	$\hat{Y}$ = -91103.882 + 6770.584X_2 + **1312.923X_3** + **1.230X_4**
15.	Bogor City	$\hat{Y}$ = -1893068.511 + **146461.747X_2** + **1933.043X_3** + **0.827X_4**
16.	Sukabumi City	$\hat{Y}$ = -1748513.402 + **134393.186X_2** + **1932.077X_3** + **0.843X_4**
17.	Bandung City	$\hat{Y}$ = -570036.273 + 40946.819X_2 + **1578.054X_3** + **1.141X_4**
18.	Cirebon City	$\hat{Y}$ = -235448.317 + 17249.778X_2 + **1447.167X_3** + **1.145X_4**
19.	Bekasi City	$\hat{Y}$ = -1959643.517 + **152135.514X_2** + **1931.183X_3** + **0.822X_4**
20.	Depok City	$\hat{Y}$ = -1936215.790 + **150127.707X_2** + **1930.009X_3** + **0.825X_4**
21.	Cimahi City	$\hat{Y}$ = -814263.820 + 59245.110X_2 + **1718.565X_3** + **1.071X_4**
22.	Tasikmalaya City	$\hat{Y}$ = -126859.451 + 9327.358X_2 + **1330.745X_3** + **1.220X_4**
23.	Banjar City	$\hat{Y}$ = -128398.947 + 9485.748X_2 + **1349.709X_3** + **1.204X_4**

Note: Bold values indicate statistical significance

4.5. Comparison of Multiple Linear Regression Model and GWR Model

A comparison was conducted between the multiple linear regression (MLR) model and the Geographically Weighted Regression (GWR) model, using the highest R^2 value and the lowest AIC value to determine the best-fitting model [15]. The comparison of the MLR and GWR models is presented in Table 10.

Table 10. Comparison of Multiple Linear Regression and GWR Models

Method	R^2	AIC
Multiple Linear Regression	0.9004	592.536
GWR	0.9665	567.222

Based on Table 10, the GWR method has a higher R^2 value of 0.9665 or 96.65% and a lower AIC value of 592.536. Therefore, it can be concluded that the GWR model is better than the multiple linear regression model.

5. CONCLUSION

Based on the analysis, Bogor Regency was identified as the region with the highest waste generation, while Banjar City had the lowest. In terms of population density, Bandung City recorded the highest value, whereas Pangandaran Regency had the lowest. The highest average years of schooling were found in Ciamis Regency, while West Bandung Regency reported the lowest. Furthermore, the largest number of people living in poverty was observed in Bogor Regency, with Banjar City having the smallest. Regarding economic indicators, Bekasi Regency had the highest Gross Regional Domestic Product (GRDP) at constant prices, while Banjar City had the lowest.

The modelling using Geographically Weighted Regression (GWR) with a Bisquare Adaptive kernel function showed a high goodness-of-fit value of 96.65%, demonstrating that the GWR model performs better than the multiple linear regression model. The analysis further revealed that the GWR model classified the regencies/cities into two groups based

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on significant variables, with 14 regencies/cities in the first group and 9 in the second group. Specifically, the waste generation model for Bogor Regency was estimated as $\hat{Y} = -1916423.555 + 148410.204X_2 + 1932.276X_3 + 0.826X_4$ with the significant variables are average years of schooling, the number of people living in poverty, and GDP at constant prices.

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