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ANALYSIS OF THE OPEN UNEMPLOYMENT RATE (OUR) ACROSS REGENCIES/CITIES IN WEST JAVA IN 2024 USING GEOGRAPHICALLY WEIGHTED REGRESSION (GWR)

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ABSTRACT

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This study aims to analyze the factors influencing the Open Unemployment Rate (OUR) in West Java Province in 2024 using the Geographically Weighted Regression (GWR) method. GWR is employed to model the spatial variation in the relationship between OUR and several independent variables, namely Labor Force Participation Rate (LFPR), the number of micro and small industrial enterprises, distance to the provincial capital (in km), and the number of general hospitals. This method is chosen for its ability to capture spatial heterogeneity that cannot be addressed by global regression models.

The study compares the performance of GWR models using three types of kernel functions: Gaussian, Bisquare, and Tricube. The results indicate that the GWR model with the Bisquare kernel function performs best, based on the Akaike Information Criterion (AIC) and the coefficient of determination (R^2). The analysis reveals that the influence of the independent variables on OUR varies across regions, and the GWR model provides lower residual values compared to the global regression model. Therefore, GWR is an effective method for uncovering spatial relationships in employment phenomena and supports regionally-based policy-making.

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1. Introduction

West Java is the most populous province in Indonesia, with a population exceeding 50.3 million in 2024. This large population presents specific challenges in the employment sector, particularly regarding the availability and quality of job opportunities. One key indicator reflecting the labor market condition in a region is the Open Unemployment Rate (OUR), defined as the percentage of the labor force actively seeking work but currently unemployed [6].

In 2024, the OUR in West Java exhibited significant variation across its districts and cities, indicating that unemployment is not spatially uniform. These disparities are influenced by region-specific characteristics such as the Labor Force Participation Rate (LFPR), the number of micro and small industrial enterprises (UMKM), accessibility to the provincial capital (measured by distance in kilometers), and the availability of public hospitals. Understanding these factors at a regional level is crucial for formulating effective and targeted employment policies [6].

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Previous studies have often relied on global regression models that assume spatial homogeneity in the relationships among variables [1]. However, these models may fail to capture local variations and spatial heterogeneity, which are critical in explaining regional labor market dynamics. Geographically Weighted Regression (GWR) addresses this issue by allowing regression parameters to vary spatially, enabling localized analysis of relationships between variables [2], [7].

Lewandowska-Gwarda [4] applied GWR to analyze unemployment in Poland, revealing significant spatial variations in the determinants of unemployment across districts. In Indonesia, Faradiba and Dhuhri [3] utilized GWR to identify factors contributing to poverty in North Sumatra Province, demonstrating the method's effectiveness in capturing spatial heterogeneity in socioeconomic data. Similarly, Prastiwi and Khoirunurrofik [5] explored the spatial spillover effects of small and medium-sized enterprise clusters on unemployment rates in Java, emphasizing the importance of spatial dependencies in regional economic analysis.

Despite these developments, there remains a gap in applying GWR to analyze unemployment in West Java using spatially localized models with various kernel functions. Therefore, this study contributes by modeling the spatial variation of OUR in West Java using GWR and evaluating the performance of three kernel functions—Gaussian, Bisquare, and Tricube—to determine the most suitable approach for localized analysis.

2. Methods

Material and Data

The data used in this study includes information on the Open Unemployment Rate (OUR) (%), Labor Force Participation Rate (LFPR) (%), the number of micro and small industrial enterprises (units), distance to the provincial capital (km), and the number of public hospitals (units) for each regency/municipality in West Java Province in 2024. In addition, geographic coordinate data of each regency/municipality is also utilized to support spatial analysis using the Geographically Weighted Regression (GWR) method.

All data used in this research were obtained from the official website of Statistics Indonesia (Badan Pusat Statistik/BPS) of West Java Province. A snapshot of the data used in this study is presented as follows:

Table 1. Descriptive Summary of Research Variables in West Java Province, 2024

Regencies /Cities	Long.	Lat.	OUR (%)	LFPR (%)	Micro-Small Industries (units)	Distance to Capital (km)	Public Hospitals (units)
Bogor	-65,950	106,8166	7.34	66.3	35524	100.14	28
Sukabumi	-69,228	106,9260	7.11	65.72	42155	119.27	9
Cianjur	-68,161	107,1424	5.99	72.63	49395	54.13	7
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
Kota Tasikmalaya	-73,274	108,2208	6.49	68.92	17234	79.19	9
Kota Banjar	-73,706	108,5342	5.44	67.22	5042	116.6	4

Source: Statistics Indonesia (BPS) West Java Province, 2024.

Research Method

This study consists of three main stages: literature review, modeling, and data analysis.

In the literature review stage, the researchers collected and studied references from books, scientific articles, journals, and other reliable sources to gain a comprehensive understanding of the basic concepts of the Geographically Weighted Regression (GWR) method, as well as various kernel weighting functions used in spatial analysis, including the Gaussian, Bisquare, and Tricube kernels.

The modeling stage was carried out by applying the GWR method to examine the spatial relationship between the Open Unemployment Rate (OUR) as the dependent variable and four independent variables: Labor Force Participation Rate (LFPR), the number of micro and small industrial enterprises, the distance to the provincial capital (in km), and the number of public hospitals in each regency/municipality of West Java Province. A Global Linear Regression model was also used for comparison, in order to evaluate the improvement and spatial sensitivity provided by GWR.

In the final stage, data analysis was conducted to evaluate and compare the performance of the GWR models with three different kernel functions. This step aimed to reveal the variation in the influence of independent variables across regions and to determine which kernel function most effectively represents the spatial variation in unemployment across West Java. This approach is expected to contribute to the formulation of more adaptive regional policies tailored to local characteristics.

Regression Model

Linear regression is one of the most fundamental techniques in statistical modeling, used to describe the relationship between a dependent variable and one or more independent variables. It assumes a linear association between the predictors and the response variable, which can be expressed through a mathematical equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + \varepsilon \quad (1)$$

Where Y is the dependent variable, $X_1, X_2, \ldots, X_k$ are the independent variables, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_k$ are the regression coefficients, and ε is the error term assumed to be normally distributed.

Linear regression is categorized into two types: simple linear regression, which involves one independent variable, and multiple linear regression, which involves two or more independent variables. The model is typically estimated using the Ordinary Least Squares (OLS) method, which minimizes the sum of squared residuals. For the OLS estimators to be valid and unbiased, several assumptions must be met, including:

- Linearity: The relationship between dependent and independent variables is linear.
- Independence: Observations are independent of each other.
- Homoscedasticity: The variance of residuals is constant across all levels of the independent variables.
- Normality: The residuals are normally distributed.

These assumptions are typically tested using various statistical diagnostics, such as:

- Shapiro-Wilk test for normality of residuals,
- Breusch-Pagan test for heteroscedasticity,
- Durbin-Watson test for autocorrelation.

While linear regression provides a global overview of relationships within a dataset, it does not account for spatial variation in the data. In cases where spatial heterogeneity is suspected, spatial regression techniques such as Geographically Weighted Regression (GWR) are more appropriate, as they allow model parameters to vary across geographical locations.

Geographically Weighted Regression

Geographically Weighted Regression (GWR) is an advanced spatial analysis method developed to address spatial heterogeneity in regression modeling. While traditional linear regression assumes that relationships between variables are constant across the study area, GWR allows these relationships to vary by location, making it more suitable for analyzing spatial data.

GWR works by estimating local regression models at each observation point in the dataset. It does so by assigning weights to nearby observations based on their geographical proximity, using a spatial kernel function. The general form of a GWR model is expressed as:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)X_{ik} + \varepsilon_i \quad (2)$$

Where:

Y_i is the dependent variable at location i

X_{ik} are the independent variables at location i

(u_i, v_i) are the coordinates of location i

$\beta_0(u_i, v_i)$ are GWR intercept

$\beta_k(u_i, v_i)$ are location-specific parameters, with $k = 1, 2,.., p$

ε_i is the error term

The spatial weighting is determined using a kernel function, which assigns greater weight to observations closer to the location being estimated. Commonly used kernels include:

- Gaussian kernel: gives weights that decline smoothly with distance,
- Bisquare kernel: gives zero weight beyond a certain distance,
- Tricube kernel: similar to bisquare but with a different weighting curve.

The bandwidth of the kernel, which controls the range of influence, can be fixed or adaptive and is usually selected through cross-validation or minimizing the Akaike Information Criterion (AIC).

According to Fotheringham et al. (2002), GWR is particularly useful when spatial non-stationarity exists, meaning that the relationship between variables changes across space. Several studies have applied GWR in socioeconomic contexts. For example, Lewandowska-Gwarda (2018) used GWR to analyze unemployment in Poland and found strong evidence of spatial variation in the factors influencing unemployment. In the Indonesian context, Faradiba and Dhuhri (2024) applied GWR to poverty analysis, showing how local characteristics significantly influence poverty levels across regions.

In summary, GWR offers a powerful alternative to global regression by capturing local patterns and providing more accurate and context-specific insights, especially for policy development that requires spatial precision.

3. Results

Descriptive Statistics

Descriptive analysis was performed on both dependent and independent variables through the use of boxplots and choropleth maps, aiming to identify potential outliers and observe spatial distribution patterns within the study region.

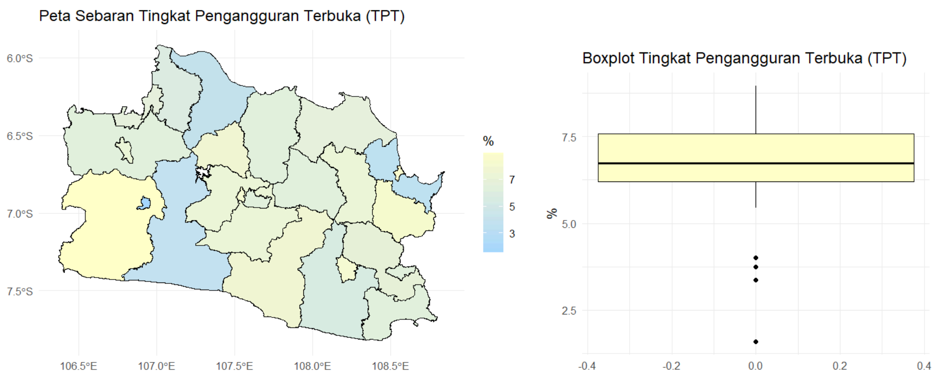

Figure 1. Gradient Map and Boxplot of OUR

The Open Unemployment Rate (OUR) in West Java shows a non-uniform spatial distribution. Several regions, such as Sukabumi, Kuningan, Purwakarta, and Garut Regencies, exhibit relatively high unemployment rates compared to other areas. The boxplot reveals the presence of a lower-end outlier, indicating that one or more districts have significantly lower unemployment rates than the majority. This suggests the existence of interregional disparities in unemployment across the province.

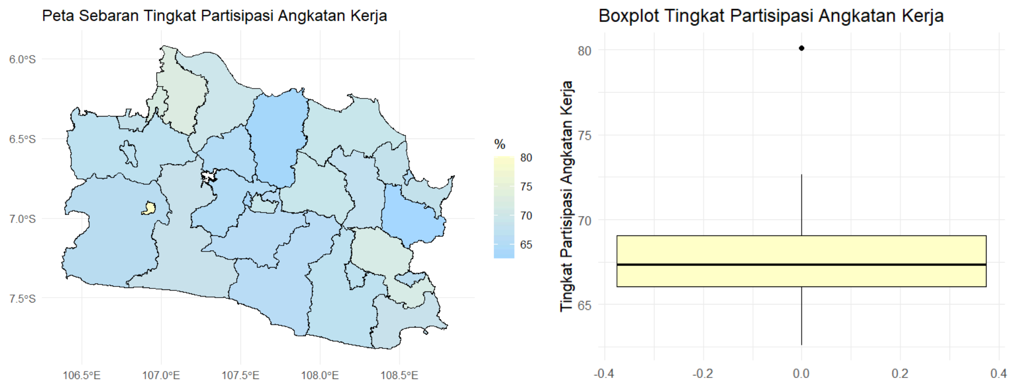

Figure 2. Gradient Map and Boxplot of LFPR

The gradient map indicates that the highest Labor Force Participation Rate (LFPR) is observed in Sukabumi City. The boxplot displays an upper outlier, which is likely attributed to Sukabumi City, suggesting that this region has a significantly higher labor force participation compared to other areas.

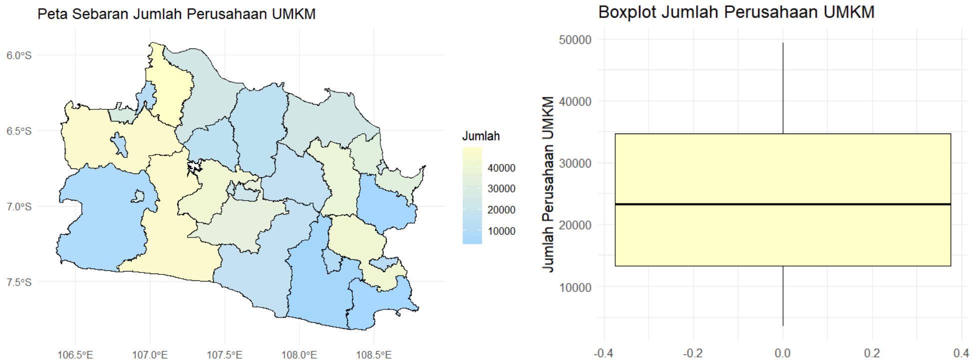

Figure 3. Gradient Map and Boxplot of Micro-Small Industries (units)

The gradient map reveals that the highest concentrations of micro and small industrial enterprises are found in Bogor Regency, Bekasi Regency, and Cianjur Regency. The boxplot indicates a relatively uniform distribution overall; however, one region approaches 50,000 units, suggesting a notably high concentration of enterprises in specific areas such as Bekasi Regency.

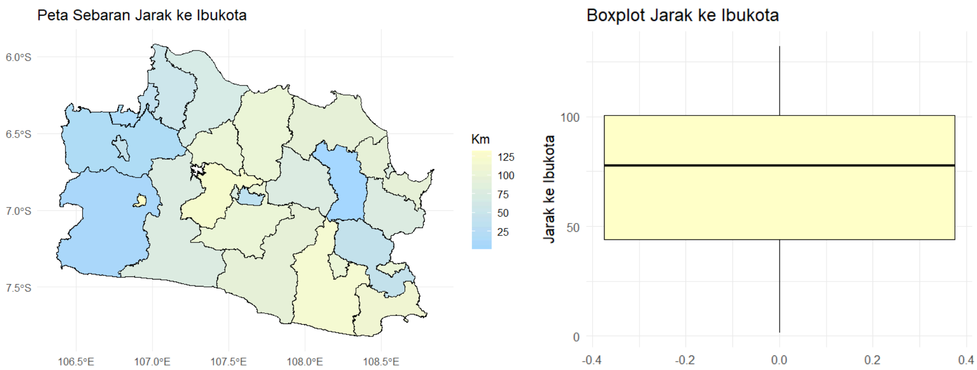

Figure 4. Gradient Map and Boxplot of Distance to Capital (km)

The gradient map shows that the regions located closest to the provincial capital, indicated by lighter blue shades, include Cimahi City, Bandung Regency, and Bandung City. In contrast, regions such as Cirebon Regency, Pangandaran Regency, and Bekasi Regency—highlighted in bright yellow—are located over 100 kilometers away. The boxplot demonstrates a fairly even distribution of distance values, with a median of approximately 90 kilometers and no extreme outliers detected.

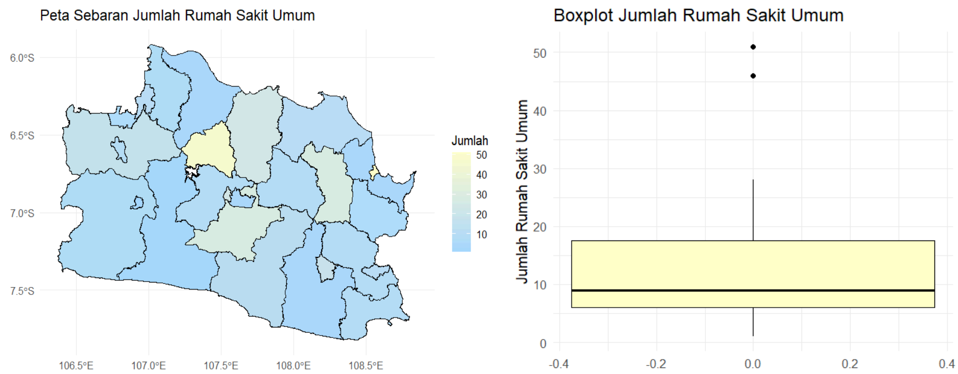

Figure 5. Gradient Map and Boxplot of Public Hospitals (units)

The gradient map indicates that Purwakarta Regency and Cirebon City have the highest number of public hospitals, as shown by the bright yellow color. The boxplot reveals an uneven distribution, with several upper outliers, suggesting that a few regions have significantly more hospital facilities compared to others in the province.

Global Methods Estimation

The results of estimating the parameters of the model OLS regression analysis produce the parameter values in Table 2.

Table 2. Output of Multiple Linear Regression

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.246e+01	4.913e+00	4.572	0.000149
LFPR	-2.146e-01	7.245e-02	-2.962	0.007202
MSI	-3.170e-05	1.668e-05	-1.900	0.070555
DTC	-1.740e-2	5.972e-03	-2.914	0.008047
PH	4.808e-02	1.917e-02	2.508	0.020029

Based on Table 2, the multiple linear regression model obtained is as follows:

$$OUR = 22.46 - 0.215LFPR - 3.17\times10^{-5}MSI - 0.0174DTC + 0.0481PH$$

The Ordinary Least Squares (OLS) regression results show that three independent variables—Labor Force Participation Rate (LFPR), Distance to Capital (DTC), and Number of Public Hospitals (PH)—are statistically significant at the 95% confidence level, with p-values less than 0.05. Among them, LFPR and DTC have negative coefficients, indicating an inverse relationship with the Open Unemployment Rate (OUR), while PH shows a positive association.

Although the number of micro and small industries (MSI) is not statistically significant at the 5% level ($p = 0.0706$), it still suggests a weak negative relationship with unemployment. These results highlight the varying strength and direction of influence that each factor has on regional unemployment in West Java within the global regression model.

Table 3. F-Test

Multiple R-Squared	F-Statistic	*p*-Value
0.6619	10.77	0.00005473

Based on Table 3, the F-statistic value is 10.77 with a p-value of 0.00005473. At a 95% confidence level ($\alpha = 0.05$), the null hypothesis H_0, which states that all regression coefficients are equal to zero (no explanatory power), is rejected since the p-value is much smaller than 0.05. This indicates that at least one of the independent variables significantly contributes to explaining the variation in the Open Unemployment Rate (OUR). The R-squared value of 0.6619 shows that approximately 66.19% of the variation in OUR can be explained by the variables in the model.

Table 4. Residual Normality

Test	Statistical W	*p*-Value
Shapiro-Wilk	0.97457	0.7248

Based on the Shapiro-Wilk normality test, the test statistic value is 0.97457 with a p-value of 0.7248. At a 95% confidence level ($\alpha = 0.05$), the null hypothesis H_0, which states that the residuals are normally distributed, is not rejected since the p-value is greater than 0.05. This indicates that the residuals of the regression model follow a normal distribution, fulfilling one of the classical linear regression assumptions.

Table 5. Autocorrelation

Test	DW Statistics	*p*-Value
Durbin-Watson	2.0466	0.4897

Based on the Durbin-Watson test, the DW statistic is 2.0466 with a p-value of 0.4897. At a 95% confidence level ($\alpha = 0.05$), the null hypothesis H_0, which assumes no autocorrelation in the residuals, is not rejected since the p-value is greater than 0.05. Furthermore, the DW statistic is close to 2, indicating that there is no significant positive or negative autocorrelation present in the residuals. Therefore, the regression model meets the assumption of residual independence.

Table 6. Heteroscedasticity

Test	BP Statistics	*p*-Value
Breusch-pagan	12.365	0.04919

Based on the Breusch-Pagan test, the test statistic is 12.365 with a p-value of 0.04919. At a 95% confidence level($\alpha = 0.05$), the null hypothesis H_0, the null hypothesis H0H_0H0, which assumes homoscedasticity (constant variance of residuals), is rejected. This result indicates the presence of heteroscedasticity in the residuals of the global regression model.

The presence of heteroscedasticity suggests that the model's explanatory power may vary across regions. Therefore, the use of the Geographically Weighted Regression (GWR) method is justified, as it is more suitable for handling spatial heterogeneity and local variations that cannot be captured by a global model.

Table 7. Multicollinearity

Variable	VIF	Conclusion
LFPR	1.398531	No multicollinearity
MSI	1.189863	No multicollinearity
DTC	1.075079	No multicollinearity
PH	1.278635	No multicollinearity

GWR Analysis

A pseudo-stepwise selection method was applied to determine the independent variables used in the Geographically Weighted Regression (GWR) model. The model selection process was carried out using three types of spatial kernel functions: Gaussian, Bisquare, and Tricube.

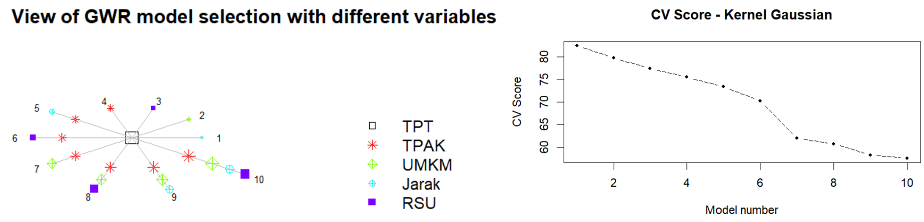

Figure 6. GWR Model Selection using Kernel Gaussian

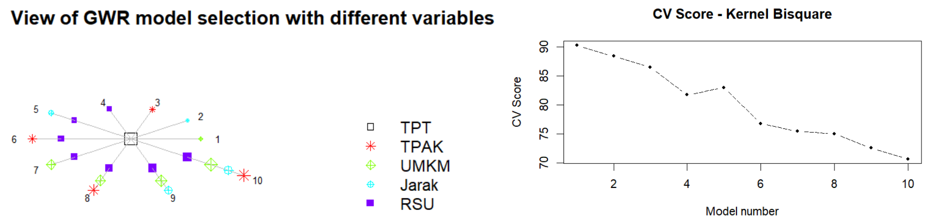

Figure 7. GWR Model Selection using Kernel Bisquare

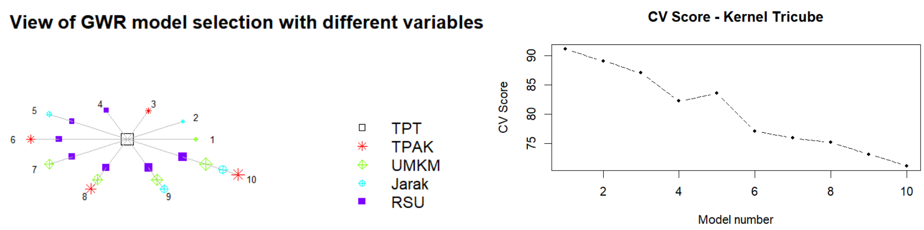

Figure 8. GWR Model Selection using Kernel Tricube

In each case, variables were added one at a time, and model performance was evaluated based on the Cross Validation (CV) score. The results showed a consistent decrease in CV values as more variables were included, indicating improved model fit. Although minor fluctuations were observed in some steps, the lowest CV was generally achieved when all five independent variables—Labor Force Participation Rate (LFPR), Number of Micro and Small Industries (MSI), Distance to the Capital (DTC), and Number of Public Hospitals (PH)—were incorporated. This suggests that all selected variables played a significant role in explaining the spatial variation of the Open Unemployment Rate (OUR) in West Java.

Following variable selection, optimal bandwidths for each kernel were determined to ensure accurate spatial weighting. The optimal bandwidths obtained were 6.1564 for the Gaussian kernel, 13.2184 for the Bisquare kernel, and 13.7348 for the Tricube kernel. These values define the spatial decay functions used in the respective kernel weighting formulas, which regulate the influence of neighboring observations based on geographic distance.

Table 8. Best Model Selection Based on AIC and R^2

Model	R^2	AIC
Global Linear Regression (OLS)	0.6618528	87.18857
GWR with Gaussian Kernel Weighting Function	0.6312112	78.49861
GWR with Bisquare Kernel Weighting Function	0.6211910	78.42530
GWR with Tricube Kernel Weighting Function	0.6100321	79.25291

Table 8 presents a comparison of model performance based on the Akaike Information Criterion (AIC) and the coefficient of determination (R^2). While the Global Linear Regression (OLS) model achieved the highest R^2 value (0.6619), it also had the highest AIC (87.1886), indicating that despite explaining more variance globally, it may not capture local spatial patterns as effectively as GWR models.

Among the Geographically Weighted Regression (GWR) models, the Bisquare kernel exhibited the lowest AIC value (78.4253), making it the best-performing model in terms of overall goodness-of-fit and model parsimony. Although its R^2 (0.6212) was slightly lower than the Gaussian kernel (0.6312), the lower AIC suggests that the Bisquare kernel provides a better balance between model complexity and fit. The superior performance of the Bisquare kernel can be attributed to its ability to assign zero weights beyond a certain distance, thus effectively localizing the influence of nearby observations and minimizing the impact of distant or potentially irrelevant data points. This makes it especially effective in capturing spatial heterogeneity in regional unemployment patterns.

Result Maps and Clustering

- *Distribution of Significant Variables*

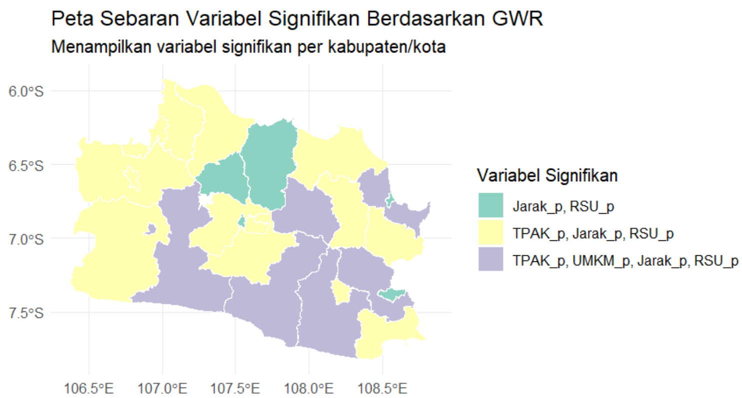

Figure 9. Distribution Map

In this study, the classification of regions was based on combinations of independent variables that showed statistically significant effects on the Open Unemployment Rate (OUR) at the 5% significance level. Although the classification initially allowed for more regional groups, the results revealed the presence of three main combinations of significant variables across districts/cities in West Java.

As shown in Figure 9, the most common group includes regions where TPAK (Labor Force Participation Rate), distance to the capital, and number of public hospitals were significant predictors of OUR. These areas are mainly concentrated in both urban and peri-urban regions with relatively high accessibility and public service infrastructure. The second group consists of regions where all four variables—TPAK, number of micro and small enterprises (UMKM), distance to the capital, and number of public hospitals—significantly influenced the unemployment rate. These areas tend to be more diverse in both geographic location and economic structure. Lastly, a smaller group includes districts where only distance to the capital and number of public hospitals were statistically significant. These are generally located further from urban centers, suggesting the importance of spatial accessibility and healthcare infrastructure in shaping unemployment levels in these regions.

- *Spatial Variability of Parameter Estimates*

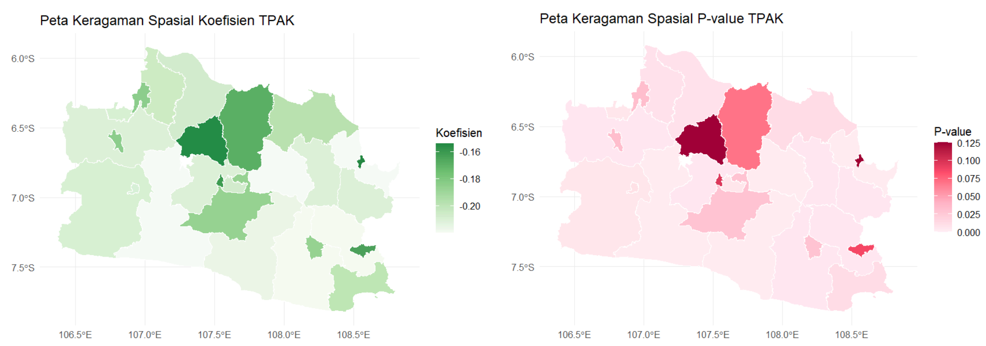

Figure 10. Spatial Variability of LFPR

Central urban areas such as Kota Bandung, Kota Bekasi, and Kota Cimahi show a lighter pink shade on the p-value map, indicating a statistically significant influence of LFPR on unemployment ($p < 0.05$). In contrast, eastern and southern regions like Kabupaten Pangandaran, Sumedang, and Kuningan display darker shades, suggesting the relationship is not significant. On the coefficient map, areas such as Cimahi and Bandung exhibit strong negative effects (bright green), while regions like Pangandaran and Majalengka show weaker associations.

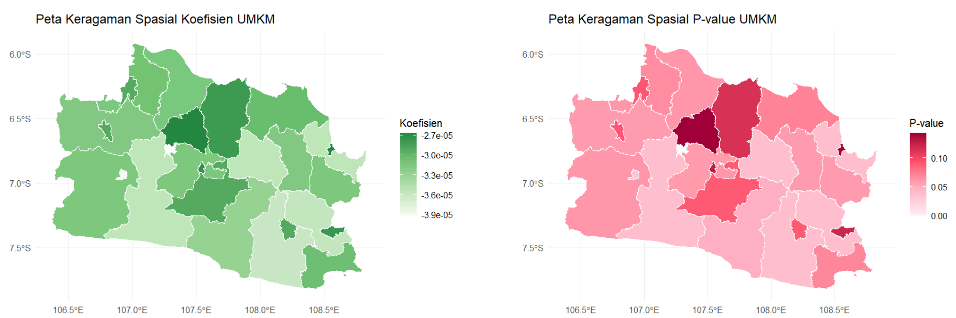

Figure 11. Spatial Variability of MSI

Lighter pink areas on the p-value map, such as Bandung, Bekasi, and Cimahi, indicate a significant relationship between the number of UMKM and unemployment ($p < 0.05$). Meanwhile, regions like Pangandaran, Subang, and Sumedang show darker shades, suggesting non-significant influence. The coefficient map highlights stronger negative effects in Cimahi and Bandung (light green), while areas like Indramayu and Kuningan show weaker impacts, implying the presence of other dominant factors.

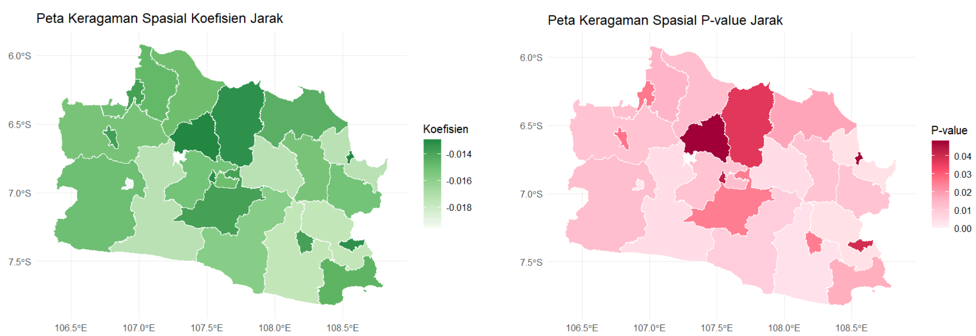

Figure 12. Spatial Variability of DTC

On the p-value map, regions such as Bandung, Bekasi, and Cimahi appear in lighter pink, indicating a statistically significant relationship between distance to the capital and unemployment ($p < 0.05$). Conversely, areas like Pangandaran, Sumedang, and Kuningan show darker red shades, suggesting a non-significant effect. The coefficient map reveals strong negative associations in cities like Cimahi and Bandung (bright green), while regions such as Indramayu, Kuningan, and Majalengka exhibit weaker effects, implying a less pronounced spatial influence.

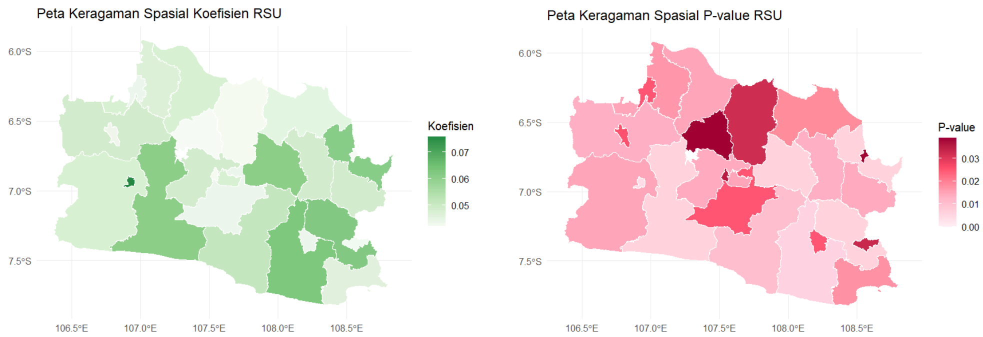

Figure 13. Spatial Variability of PH

Lighter pink areas on the p-value map, such as Bandung, Bekasi, and Cimahi, indicate a significant relationship between the number of public hospitals (PH) and unemployment ($p < 0.05$). In contrast, darker regions like Pangandaran, Sumedang, and Kuningan show non-significant effects. The coefficient map reveals stronger positive associations in cities like Bandung and Bekasi (dark green), while areas such as Pangandaran, Garut, and Kuningan display weaker impacts, suggesting a less pronounced role of PH in influencing unemployment levels.

- *Spatial Variability of Residuals*

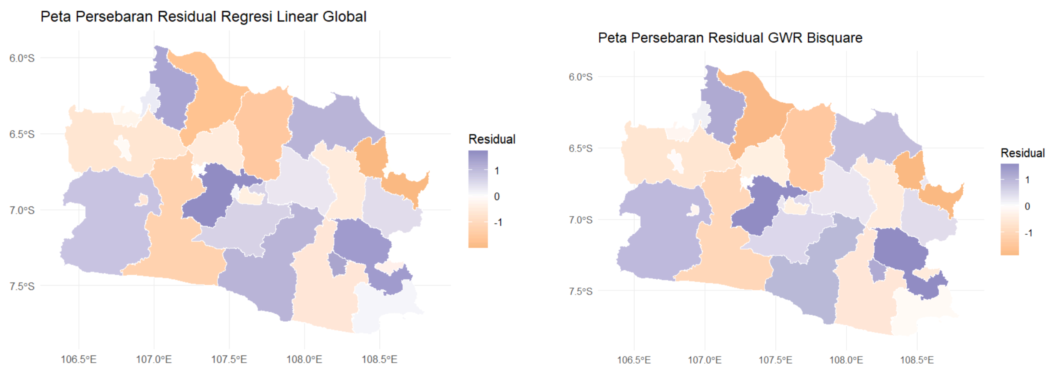

Figure 14. Residuals Map

The residual maps from both the OLS and GWR models provide a visual representation of the prediction accuracy regarding the Open Unemployment Rate (OUR) in West Java Province for the year 2024. In these maps, red areas indicate negative residuals, meaning that the predicted value is higher than the actual OUR, while blue areas represent positive residuals, where the predicted value is lower than the actual.

According to the residual summary, the global linear regression model (OLS) has a residual range of 0.012 to 1.996, whereas the GWR Bisquare model produces a narrower range of 0.029 to 1.876. This indicates that the GWR model reduces prediction errors more effectively and better captures local spatial variations across the regencies and cities in West Java. Therefore, GWR proves to be a more accurate model for analyzing spatially heterogeneous phenomena such as regional unemployment.

4. Discussions

The global model using Ordinary Least Squares (OLS) regression showed that several independent variables—including Labor Force Participation Rate (LFPR), Distance to Capital (DTC), and Number of Public Hospitals (PH)—had statistically significant effects on the Open Unemployment Rate (OUR) in West Java. However, this global model assumes spatial homogeneity and fails to account for the spatial heterogeneity observed across regencies and cities.

To address this limitation, the Geographically Weighted Regression (GWR) method was employed, enabling local modeling of variable influence. The results demonstrated that the relationship between each independent variable and OUR varied significantly across regions. Among the three kernel functions tested, the Bisquare kernel produced the best performance based on the lowest Akaike Information Criterion (AIC = 78.4253), despite having a slightly lower R^2 compared to the Gaussian kernel. This highlights the Bisquare kernel's superior ability to localize regression effects and capture spatial nuances in the data.

The spatial distribution of significant variables further revealed three dominant patterns of influence across the study area. LFPR, DTC, and PH were most commonly significant in urban and peri-urban areas. Meanwhile, full variable significance was observed in more economically diverse regions, and in some remote areas, only DTC and PH showed consistent influence. Additionally, spatial coefficient maps uncovered varied magnitudes and directions of influence—stronger negative associations of LFPR and DTC in cities like Bandung and Cimahi, and stronger positive associations of PH in more urbanized regions.

The residual maps supported these findings by showing lower prediction errors in the GWR model compared to the OLS model, underscoring the effectiveness of GWR in modeling region-specific dynamics in unemployment.

5. Conclusion

This study highlights the advantages of using Geographically Weighted Regression (GWR) to explore spatially varying relationships between the Open Unemployment Rate (OUR) and its predictors in West Java Province. Unlike the global OLS model, GWR captures localized variations, offering a more nuanced understanding of unemployment dynamics. Among the kernel functions tested, the Bisquare kernel demonstrated the best model performance, providing both accuracy and parsimony.

The spatial heterogeneity in variable significance and coefficient magnitude emphasizes the need for region-specific policy interventions. Policymakers should consider localized labor force characteristics, economic infrastructure, and spatial accessibility when designing unemployment reduction strategies. Incorporating spatial analysis techniques like GWR can lead to more targeted, effective, and equitable employment policies.

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