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# Application of the Spatial Durbin Panel Model and Geographically Weighted Panel Regression on Poverty Data in West Java Province*

Anis Sulistiyowati[1], Mohammad Masjkur[2‡], and Budi Susetyo[3]

[1,2,3]School of Data Science, Mathematics, and Informatics, IPB University, Indonesia
‡Corresponding author: masjkur@apps.ipb.ac.id



**Abstract**

Poverty is one of the priority issues in the Sustainable Development Goals. In 2024, West Java Province became the province with the second-highest number of people living in poverty in Indonesia. This study aims to identify the variables that significantly affect the percentage of people living in poverty in districts/cities of West Java Province from 2019 to 2023, using the spatial Durbin panel model and geographically weighted panel regression. The data used is secondary data on poverty indicators in West Java Province from 2019 to 2023, sourced from Statistics Indonesia of West Java. The spatial Durbin panel model developed in this study is a fixed-effects spatial Durbin panel model. The model shows that average years of schooling and expenditure per capita have significant effects. In addition, the spatial lags of the percentage of households living in appropriate housing, the percentage of the population covered by local health insurance, and average years of schooling also have significant effects. The geographically weighted panel regression model, estimated using a fixed effect panel regression with a Gaussian fixed kernel as the optimal weighting function, produces distinct models for each region. The average year of schooling is the dominant factor influencing the percentage of people living in poverty in districts/cities in West Java Province.

**Keywords**: fixed effect, geographically weighted panel regression, poverty, spatial Durbin panel model, spatial panel data.

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## 1. Introduction

The Indonesian government continues to strive to achieve the Sustainable Development Goals (SDGs) targets, which are global and national commitments aimed at improving the welfare of its people (Suharyani & Djumarno, 2023). The SDGs include 17 goals, one of which is the first goal, namely eradicating poverty by ending all forms of poverty everywhere (Pertiwi, 2023). Poverty is a major challenge for developing countries, including Indonesia. The poverty level of a region in Indonesia can be seen from one of the macro poverty indicators, namely the percentage of poor people, which is the ratio of the number of poor people to the total population in a region (BPS, 2024a).

In 2024, West Java Province was recorded as the province with the second-largest number of poor people in Indonesia, with 3,668,350 people, representing a poverty rate of 7.46% of the total population. Although the percentage of poor people is below the national percentage, 13 of the 27 regencies/cities in West Java Province still have a rate of poor people above the national percentage, and there is a reasonably high disparity between regencies/cities. Based on BPS data, in 2024, Depok City had a relatively low poverty rate of 2.34%. Meanwhile, several other regions still had a relatively high percentage of people living in poverty, including Indramayu Regency (11.93%), Kuningan Regency (11.88%), and Tasikmalaya City (11.10%).

The disparity in the percentage of poor people between districts/cities in West Java Province suggests that various factors cause poverty in these areas. Therefore, an analysis is necessary to examine the factors that influence it. One commonly used analytical method is classical linear regression. However, this method is inaccurate if the data contains spatial effects in the form of spatial dependency and heterogeneity. Spatial dependency refers to the condition in which one observation unit influences another, while spatial heterogeneity refers to the inconsistency in the relationship between variables at different locations (Yasin et al., 2020). Sometimes, in a study, it is not enough to use data from a single time period; therefore, it is necessary to use panel data that includes many of the same individual units and is observed over several specific time periods (Ahmaddien & Susanto, 2020).

An analysis method that can overcome the effects of spatial dependency on panel data is spatial panel regression analysis, such as the spatial lag panel model (SLPM) and the spatial error panel model (SEPM). In addition to these two models, there is the spatial Durbin panel model (SDPM), which can account for spatial dependency in the response variable and explanatory variables (Gao et al., 2023; Xu et al., 2023). The effects of spatial heterogeneity on panel data can be addressed using geographically weighted panel regression (GWPR). GWPR is a development of the geographically weighted regression (GWR) model for modeling panel data (Musella et al., 2023; Salim et al., 2025).

Alvitiani et al. (2019) employed a spatial Durbin panel model, specifically the SDPM model with a fixed effects panel regression, to model poverty data for Central Java Province and obtained a model with an $R^2$ of 0.9995. Febrianti et al. (2023) modelled the crime rate in Indonesia using the GWPR method, obtaining the best GWPR model with a fixed effect panel regression model and a Gaussian adaptive kernel weighting function, with an $R^2$ value of 0.6989.

The disparity in the percentage of people living in poverty between districts/cities in West Java Province is caused by various factors. On this basis, the spatial Durbin panel model is used to investigate the spatial effect of factors on the percentage of people living in poverty considering the spatial dependency. The SDPM can examine the spatial spillover effect between regions and the marginal effects of factors from the surrounding regions. On the other hand, the geographically weighted panel regression takes into account the spatial heterogeneity. The GWPR explores the space-time determinants of the percentage of people living in poverty and the spatial localized variability of predictors. This study aims to identify variables that significantly affect the percentage of people living in poverty in West Java Province from 2019 to 2023, using the spatial Durbin panel model and the geographically weighted panel regression.

## 2. Methodology

### 2.1 Materials and Data

This study uses secondary data sourced from the Central Statistics Agency (BPS) of West Java Province. The data is in the form of panel data covering 27 regencies/cities in West Java Province between 2019 and 2023 (https://jabar.bps.go.id/id). The dataset contains a total of 135 observations, one response variable, seven explanatory variables, and district/city coordinate variables in the form of longitude and latitude data. Details of the variables used in the study are presented in Table 1.

Table 1: Variables used in the research

| Variable | Information | Unit | Library Sources |
|---|---|---|---|
| Y | Percentage of the poor population | Percent | BPS (2024b) |
| X1 | Open unemployment rate | Percent | Handayani (2023) |
| X2 | Percentage of households occupying habitable housing | Percent | Asnawi et al. (2020) |
| X3 | Percentage of households with access to proper sanitation | Percent | Andrianus & Alfatih (2023) |
| X4 | Percentage of population with regional health insurance | Percent | Banito et al. (2022) |
| X5 | Gross regional domestic product at current prices | Billions of rupiah | Prawitrisari et al. (2022) |
| X6 | Average length of schooling | Year | Mirnayanti et al. (2024) |
| X7 | Per capita expenditure | Thousand rupiah /person/year | Puteri & Marwan (2023) |
| *u, v* | District/city coordinates | Longitude and latitude | - |

## 2.2 Research methods

### 2.2.1 Spatial Durbin Panel Model (SDPM)

The fixed effect spatial Durbin panel model defined as follows,

$$y_{it} = \beta_0 + \rho \sum_{i=1}^{n} w_{ij} y_{it} + \sum_{k=1}^{p} \beta_k x_{kit} + \sum_{k=1}^{p} \theta_k w_{ij} x_{kit} + \mu_i + \varepsilon_{it}; \quad (1)$$

where $y_{it}$, $x_{kit}$, and $\varepsilon_{it}$ are, respectively, the dependent variable, the $k$−th explanatory variable, and the error term at the *i*-th location at time *t*; *k* is the number of explanatory variables, $w_{ij}$ is the spatial weight matrix, $\beta_k$ is the coefficient of the $k$−th variable for the *i*-th unit at time *t*, $\theta_k$ the coefficients for the spatially lagged covariates $w_{ij} x_{kit}$, while $\beta_0$ is the intercept, $\rho$ denotes the spatial correlation coefficient, $\mu_i$ is *i*-th individual unit specific effect, $i = 1,2, \dots, n,\ t = 1,2, \dots, T$ (Gao et al., 2023; Xu et al., 2023).

### 2.2.2 Geographically Weighted Panel Regression (GWPR)

The GWPR with fixed effects can be written as follows,

$$y_{it} = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{kit} + \varepsilon_{it}; k = 1,2, \dots, p \quad (2)$$

where $u_{it}$, $v_{it}$ are the geographical coordinates for the *i*-th location at time *t*; $\beta_k(u_{it}, v_{it})$ is the coefficient of the $k$−th explanatory variable for the *i*-th unit at time *t*,while $\beta_0(u_{it}, v_{it})$ is the intercept that denotes the time-invariant fixed effects, *k* is the number of explanatory variables, $i = 1,2, \dots, n,\ t = 1,2, \dots, T.$, all other variables are as in (1) (Musella et al., 2023; Salim et al., 2025).

### 2.2.3 Data analysis

Data analysis was conducted through the following stages.

a. Conduct data exploration to understand patterns, structures, and characteristics of the data. Data exploration encompasses thematic maps, box plots, and correlation matrices. Multicollinearity testing, which occurs when two or more explanatory variables in a regression model have a strong linear relationship, is performed using the Variance Inflation Factor (VIF). The following is the VIF calculation formula (Gujarati, 2003):

$$VIF_k = \frac{1}{1 - R_k^2} \quad (3)$$

with $R_k^2$ is the coefficient of determination between the explanatory variable $\mathrm{X}_k$ and other explanatory variables, $k = 1, \dots, p$.

b. Selecting the best panel regression model using the Chow test and the Hausman test.
   1) The Chow test is used to distinguish between the common effects and fixed effects models. The main difference between the two models lies in the interception of each individual unit. The intercept of the common effects model is constant across all individual units. In contrast, the fixed effects model accommodates differences in individual unit characteristics through the intercept. The basis of the Chow test is the assumption that each unit behaves the same, which is likely unrealistic because each individual unit can behave differently. The following are the hypotheses of the Chow test:

(Caraka & Yasin, 2017):
$H_0$: $\beta_{0_1} = \beta_{0_2} = \cdots = \beta_{0_N} = \beta_0$ (common effect model)
$H_1$: there is at least one $\beta_{0_i}$ difference (fixed effect model)
Test statistics:

$$F_C = \frac{RSS_1 - RSS_2/(N-1)}{RSS_2/(NT-N-p)} \tag{4}$$

where $RSS_1$ is the residual sum of squares from the estimation results of the common effect model and $RSS_2$ is the residual sum of squares from the estimation results of the fixed effect model, $p$ is the number of explanatory variables. $H_0$ is rejected if $F_C > F_{(N-1;NT-N-p;\alpha)}$ or p-value $< \alpha$, which means the selected panel regression model is a fixed effect model. If $H_0$ is accepted, it means the selected panel regression model is a common effects model.

2) The Hausman test is used to determine whether to select a fixed effects or random effects model. The difference between fixed-effects and random-effects models lies in the assumed relationship between individual effects and explanatory variables. In the fixed effect model, individual effects (μ) are assumed to be correlated with the explanatory variables. Conversely, in the random effect model, individual effects (μ) are assumed to be uncorrelated with the explanatory variables. The basis of the Hausman test is the fixed effect model, which contains a trade-off element: the loss of degrees of freedom that results from including dummy variables. The random effect model, on the other hand, accounts for the absence of violations of the assumptions for each error component. The following are the hypotheses of the Hausman test (Caraka & Yasin, 2017):
$H_0$: $corr(x_{it}, \varepsilon_{it}) = 0$ (random effect model)
$H_1$: $corr(x_{it}, \varepsilon_{it}) \neq 0$ (fixed effect model)
Test statistics:

$$\chi^2(K) = (\boldsymbol{b} - \boldsymbol{\beta})'[Var(\boldsymbol{b} - \boldsymbol{\beta})]^{-1}(\boldsymbol{b} - \boldsymbol{\beta}) \tag{5}$$

where $\boldsymbol{b}$ is the slope coefficient vector of the random effect model and $\boldsymbol{\beta}$ is the slope coefficient vector of the fixed effect model. H0 is rejected if $\chi^2 > \chi^2_{(K,\alpha)}$ or the p-value $< \alpha$, which means the selected panel regression model is a fixed effect model. If H0 is accepted, it means the chosen panel regression model is a random effect model.

c. Examining spatial effects on data.
   1) Constructing a spatial weighting matrix using a distance approach based on *k*-nearest neighbors (*k*-NN). The value of *k* is selected based on the value of k that produces the optimum Moran's index value.
   2) Testing spatial dependency using the spatial autocorrelation test, namely the Moran index for the response variable and the explanatory variable on an annual basis, namely for each year from 2019 to 2023. The following is the hypothesis of the Moran index test:(Goodchild, 1986):
   $H_0$: $I = 0$ (no spatial autocorrelation)
   $H_1$: $I \neq 0$ (there is spatial autocorrelation)

Test statistics:

$$Z_{hitung} = \frac{I - E(I)}{\sqrt{var(I)}} \tag{6}$$

with

$$I = \frac{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left((y_i - \bar{y})(y_j - \bar{y})\right)\right)}{\frac{\sum_{i=1}^{N}(y_i - \bar{y})^2}{N}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} = \frac{\boldsymbol{e'We}}{\boldsymbol{e'e}} \tag{7}$$

$$var(I) = \frac{N^2\left(\frac{1}{2}\sum_{i\neq j}^{N}\left(w_{ij} + w_{ji}\right)^2\right) - N\left(\sum_{i\neq j}^{N}(w_{i0} + w_{0i})^2\right) + 3\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)^2}{(N^2 - 1)\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)^2} \tag{8}$$

with

$$w_{i0} = \sum\nolimits_{j=1}^{N} w_{ij}\ ;\ w_{0i} = \sum\nolimits_{j=1}^{N} w_{ji} \tag{9}$$

with $I$ is the Moran Index, $n$ the number of locations (districts/cities), $y_i$ the observed value at the $i$-th location, $y_j$ the observed value at the $j$-th location, $\bar{y}$ the average of the observed values, and $w_{ij}$ the spatial weighting matrix elements of the $i$-th and $j$-th regions. $\boldsymbol{e}$ is the residual vector and $\boldsymbol{W}$ is the spatial weighting matrix. $H_0$ is rejected if $|Z\quad| > Z_{\alpha/2}$ or p-value $< \alpha$, which means there is spatial autocorrelation.

3) Examining spatial heterogeneity using the Breusch-Pagan test. The following are the hypotheses of the Breusch-Pagan test (Alica et al., 2025):
$H_0$: $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_N^2$ (no spatial heterogeneity)
$H_1$: there is at least one $\sigma_i^2 \neq \sigma^2$ (there is spatial heterogeneity)
where $\sigma_i^2 = f(a_1 + a_2X_{2i} + \cdots + a_kX_{ki})$. Test statistics:

$$BP = \left(\frac{1}{2}\right)\boldsymbol{f'Z(Z'Z)^{-1}Z'f} \tag{10}$$

with $\boldsymbol{f} = (f_1, f_2, \ldots, f_N)$; $\boldsymbol{f_i} = (\frac{(e_i^2)}{\sigma^2} - 1), e_i = y_i - \hat{y_i}$ is the least square residual of the individual unit, and $\boldsymbol{Z}$ is a normalized matrix of size $N \times (p+1)$ that has been standardized for each observation. $H_0$ is rejected if $BP > \chi_p^2$ or p-value $< \alpha$, which means there is spatial heterogeneity.

d. Perform spatial modeling of SDPM.
   1) If the selected panel regression model is a fixed effects model, then the model built is a fixed effects SDPM model. If the chosen panel regression model is a random effects model, then the model built is a random effects SDPM model. Model parameter estimation uses the maximum likelihood method.
   2) Conducting residual assumption checks, including normality, spatial heterogeneity, and residual spatial autocorrelation.
      a) Normality of residuals
      Testing the normality of residuals using the normal Q-Q plot and the Kolmogorov-Smirnov test. If the residuals are normally distributed, then the points on the normal Q-Q plot will be located around a linear line (Montgomery et al., 2012). The following is the Kolmogorov Smirnov test hypothesis (Dimitrova et al., 2020):

$H_0: \varepsilon(x) = F^*(x)$ (normally distributed residuals)
$H_1: \varepsilon(x) \neq F^*(x)$ (residuals are not normally distributed)
Test statistics:

$$D = sup_x|F^*(x) - \varepsilon(x)| \tag{11}$$

with $sup$ is the maximum value, $F^*(x)$ is the normal distribution function whose mean and standard deviation are known, $\varepsilon(x)$ and is the distribution function of the residuals taken from a random sample. $H_0$ is rejected if the value $D > D_{table}$ or p-value $< \alpha$ means the residuals are not normally distributed.

b) Spatial heterogeneity
Spatial heterogeneity testing uses the Breusch-Pagan test. The test statistic used follows the formula stated in Equation (10).

c) Residual spatial autocorrelation
The residual spatial autocorrelation test uses the Moran index. The test statistic used follows the formula stated in equation (7).

3) Model interpretation involves explaining the explanatory variables that are proven to have a significant influence on the response variable.

e. Performing GWPR modeling.
1) Perform data transformation using the "within" transformation if the selected best panel regression model is a fixed effects model. The transformation is performed by averaging the time series observations for each individual unit, then transforming the variables by subtracting them from the corresponding time series average (Wooldridge, 2002).
2) Select the best spatial weighting matrix based on the smallest Akaike Information Criterion (AIC) value and the largest $R^2$. The following formula is used to calculate the AIC value (Greene, 2020):

$$AIC = -2\log(\hat{\mathrm{L}}) + 2p \tag{12}$$

where $p$ is the number of regression parameters and $2\log(\hat{\mathrm{L}})$ is the value of the log-likelihood function for the parameter estimate. Meanwhile, the formula for calculating $R^2$ is as follows (Montgomery et al., 2012):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{13}$$

3) Estimating GWPR model parameters.
4) Parameter testing and model interpretation by explaining the explanatory variables that are proven to have a significant influence on the response variable.

## 3. Results and Discussion

### 3.1 Data Exploration

Figure 1 illustrates the change in the percentage of people living in poverty in West Java Province from 2019 to 2023. The darker the colour on the map, the higher the percentage of people living in poverty. In 2019, most areas in West Java Province were in the middle poverty category. In 2020, there was an increase in the percentage of people living in poverty in several regions, particularly in the southern and eastern areas, including Tasikmalaya Regency, Ciamis Regency, Garut Regency, and their surrounding areas. This increase coincided with the Covid-19 pandemic, which reduced economic activity in Indonesia. In 2021, the distribution of high poverty rates persisted and expanded to several other regions. Northern areas, such as Indramayu Regency and Subang Regency, showed an increase in the percentage of people living in poverty. However, in different areas, such as Bandung City and Depok City, the percentage of poor people remained in the low poverty category. In 2022, in several western and northern regions, such as Bekasi Regency and Bogor Regency, the percentage of people living in poverty decreased. However, most southern areas, including Garut Regency and Tasikmalaya Regency, still had a high percentage of people living in poverty. The year 2023 is almost similar to the previous year.

Based on the five boxplots of the percentage of poor people in West Java Province from 2019 to 2023 in Figure 2, the data distribution is relatively symmetrical and shows no outliers, as indicated by the absence of points outside the whisker lines. All values fall within the minimum and maximum ranges, and there are no extreme observations. The distribution pattern between years appears similar, as indicated by the relatively consistent shape and size of the boxplots. There is a slight fluctuation from year to year, as noted in the position of the median (the centre line of the boxplot).

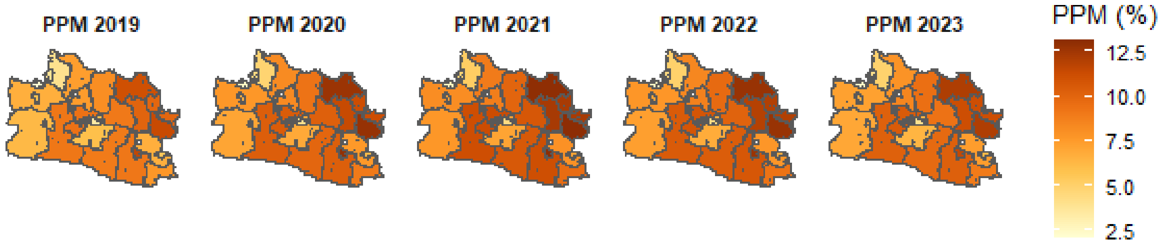


Figure 1: Thematic map of the distribution of PPM in West Java 2019–2023

This suggests that the primary differences in the data primarily stem from variations between individuals (districts/cities) rather than changes over time.

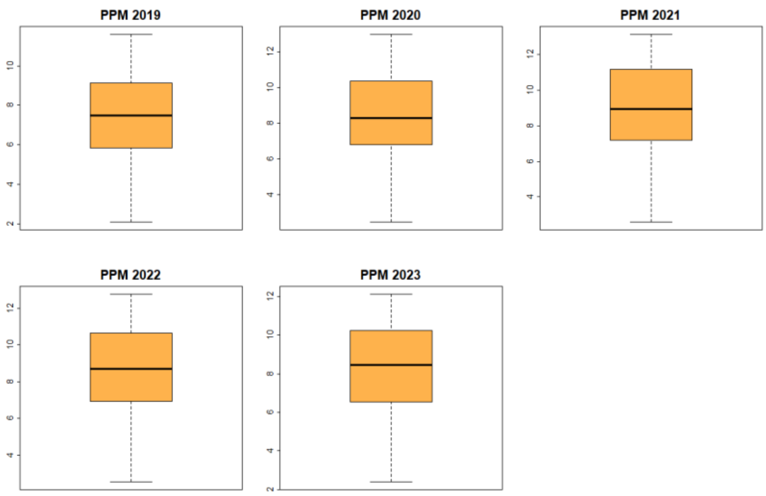


Figure 2: Boxplot of the percentage of the poor population in West Java Province in 2019–2023

Data exploration was also conducted using a correlation matrix plot to identify the relationship between the variables used in this study. The results of the data exploration, as presented in a correlation matrix, are shown in Figure 3. The variable per capita expenditure (X7) exhibits the strongest negative correlation with the percentage of people living in poverty (Y); the higher the per capita expenditure, the lower the percentage of people living in poverty. In addition, the variables of the open unemployment rate (X1), the percentage of households with access to proper sanitation (X3), the percentage of the population with regional health insurance (X4), the gross regional domestic product at current prices (X5), and the average length of schooling (X6) are also negatively correlated with the percentage of poor people. The variable percentage of households occupying habitable houses (X2) is positively correlated; the higher the percentage of households occupying habitable houses, the higher the percentage of people living in poverty.

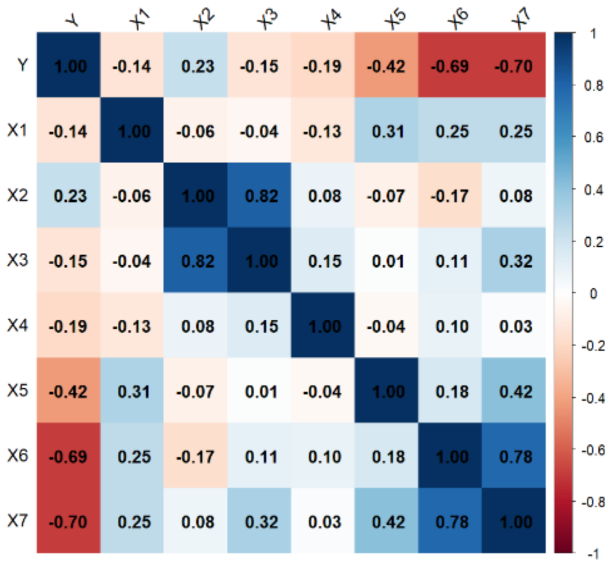

Figure 3: Correlation matrix plot

Multicollinearity testing is the final step in data exploration. Multicollinearity indicates dependencies between explanatory variables, which can affect the accuracy of estimating regression coefficients. Dependency testing can be performed using the VIF value. A VIF value exceeding 10 indicates the presence of dependencies between the explanatory variables (Montgomery et al., 2012). Table 2 presents the VIF values for each explanatory variable. The table shows that the VIF values for all explanatory variables are less than 10, indicating that there is no dependency between the explanatory variables used.

Table 2: VIF value for each explanatory variable

| **Explanatory Variables** | X1 | X2 | X3 | X4 | X5 | X6 | X7 |
|---|---|---|---|---|---|---|---|
| **VIF value** | 1.2024 | 3.9231 | 4.0256 | 1.0740 | 1.4966 | 3.6106 | 4.1353 |

### 3.2 Panel Regression Model Selection

Three models were developed: the common effect, fixed effect, and random effect models. The best panel regression model was selected using the Chow and Hausman tests. The Chow test selects the common effect or fixed effect model, while the Hausman test selects the fixed effect or random effect model. The results of the Chow and Hausman tests are presented in Table 3.

Table 3: Results of the test for selecting the best panel regression model

| Test | Test statistics | p-value | Decision |
|---|---|---|---|
| Chow Test | 53.19 | 0.00* | Reject H0 |
| Hausman test | 120.97 | 0.00* | Reject H0 |

Based on Table 3, the p-value of the Chow test is less than the significance level of 0.05, indicating $H_0$ rejection, which means the selected model is a fixed effects model. Next, a Hausman test is performed because the chosen model in the Chow test is a fixed effect model. The p-value of the Hausman test is less than the significance level of 0.05, so H0 is rejected, meaning the selected model is a fixed effect model. It can be concluded that the best panel data regression model is the fixed effect model.

### 3.3 Spatial Effect Examination

Two spatial effects are examined: spatial dependency and heterogeneity. Spatial dependency was tested using a spatial autocorrelation test through the Moran index test. The spatial weighting matrix for the response variables across all time periods was based on k-nearest neighbours (k-NN). The selection of the k value was determined based on the largest Moran index value. Based on Figure 4, the value of k = 3 produces the largest Moran index value, which is 0.9479. Therefore, k = 3 was chosen as the optimum k value in forming the spatial weighting matrix. Next, the examination of spatial dependency using the spatial autocorrelation test, as measured by the Moran index, was conducted on both the response variables and explanatory variables. The Moran index test used a k-NN weighting matrix with k = 3 (3-NN). Table 4 presents the results of the Moran index test.

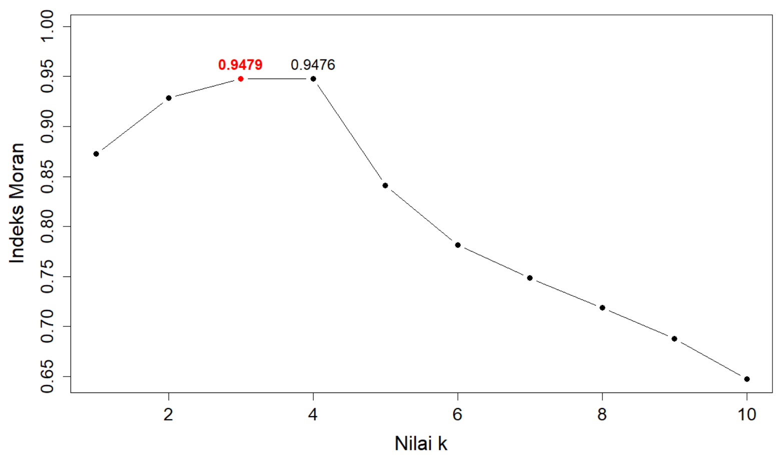


Figure 4: Selection of values for k-NN spatial weights$k$

Table 4: Results of Moran's index testing of response variables and explanatory variables

| Variable | | Year | | | | |
|---|---|---|---|---|---|---|
| | | 2019 | 2020 | 2021 | 2022 | 2023 |
| Y | Moran's Index | 0.4829* | 0.4843* | 0.4979* | 0.5125* | 0.5001* |
| | p-value | 0.0007 | 0.0007 | 0.0005 | 0.0004 | 0.0005 |
| X1 | Moran's Index | 0.4097* | 0.6180* | 0.6726* | 0.6199* | 0.5290* |
| | p-value | 0.0030 | 0.0000 | 0.0000 | 0.0000 | 0.0002 |
| X2 | Moran's Index | 0.6874* | 0.6832* | 0.6156* | 0.6455* | 0.6832* |
| | p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| X3 | Moran's Index | 0.6022* | 0.5091* | 0.5390* | 0.4943* | 0.6173* |
| | p-value | 0.0000 | 0.0004 | 0.0002 | 0.0006 | 0.0000 |
| X4 | Moran's Index | -0.1293 | 0.2051* | 0.3246* | 0.3045* | 0.0721 |
| | p-value | 0.7312 | 0.0438 | 0.0016 | 0.0042 | 0.2107 |
| X5 | Moran's Index | 0.2832* | 0.2771* | 0.2861* | 0.2860* | 0.2861* |
| | p-value | 0.0184 | 0.0204 | 0.0176 | 0.0178 | 0.0178 |
| X6 | Moran's Index | 0.2729* | 0.2791* | 0.2659* | 0.2339* | 0.2310 |
| | p-value | 0.0288 | 0.0264 | 0.0319 | 0.0487 | 0.0503 |
| X7 | Moran's Index | 0.2977* | 0.2798* | 0.2991* | 0.3072* | 0.2914* |
| | p-value | 0.0156 | 0.0206 | 0.0152 | 0.0133 | 0.0172 |

*) significant at $\alpha = 0.05$

Based on Table 4, it can be seen that the results of the Moran index test for variables Y, X1, X2, X3, X4, X5, X6, and X7 have a p-value less than the significance level of 0.05. This indicates that there is spatial autocorrelation in the response and explanatory variables. Based on these results, SDPM modelling can be employed to mitigate spatial dependencies in both the response and explanatory variables.

Spatial heterogeneity was tested using the Breusch-Pagan test. The test statistic value was 25.6930 with a p-value of 0.0006. The p-value is less than the significance level of 0.05, thus rejecting the null hypothesis (H0). This suggests that there is sufficient evidence to indicate heterogeneity exists between the observed locations. It can be said that the percentage of people living in poverty varies significantly between districts/cities in West Java Province. Based on these results, GWPR modeling can be used to address spatial heterogeneity.

### 3.4 Spatial Durbin Panel Modeling

Based on the Moran index test in Table 4, the Moran index of both the response variable and the explanatory variable has a p-value less than 0.05, indicating that spatial SDPM modelling is necessary. Meanwhile, Table 3 indicates that the selected panel regression model is a fixed-effects model. Therefore, a fixed effect spatial Durbin panel model will be built. Model parameter estimation is carried out using the maximum likelihood method. The spatial weighting matrix used is the 3-NN weighting matrix. The results of parameter estimation are presented in Table 5. Parameters with p-values less than 0.05 have a significant effect at the 0.05 significance level. The parameter $\rho$ which is the spatial lag autoregression coefficient value is positive and significant, indicating that the real impact of the explanatory variable on the increase/decrease in the percentage of poor people in a district/city in West Java is associated with an increase/decrease in the percentage of poor people in neighboring districts/cities and in turn will also have an impact on the increase/decrease in the percentage of poor people in that district/city. The explanatory variables that have a significant influence are the average length of schooling (X6) and per capita expenditure (X7). In addition, the lag of the variables of the percentage of households occupying habitable houses (X2), the percentage of the population with regional health insurance (X4), and the average length of schooling (X6) also have a significant influence at the 0.05 level of significance.

Table 5: Parameter estimates of the SDPM fixed effect model

| Parameter | Coefficient | p-value |
|---|---|---|
| $\rho$ | 0.1890 | 0.0022* |
| $\beta_1$ | 0.0627 | 0.4974 |
| $\beta_2$ | 0.0176 | 0.671 |
| $\beta_3$ | -0.0240 | 0.5125 |
| $\beta_4$ | -0.0058 | 0.3983 |
| $\beta_5$ | 0.00001 | 0.1404 |
| $\beta_6$ | 1.4439 | 0.0047* |
| $\beta_7$ | -0.0013 | 0.0044* |
| $\theta_1$ | 0.1133 | 0.2857 |
| $\theta_2$ | 0.0903 | 0.0369* |
| $\theta_3$ | -0.0296 | 0.4379 |
| $\theta_4$ | -0.0240 | 0.0096* |
| $\theta_5$ | -0.00002 | 0.0776 |
| $\theta_6$ | -1.6553 | 0.0029* |
| $\theta_7$ | 0.0007 | 0.1730 |

*) significant at $\alpha = 0.05$

The model has a coefficient of determination (R2) value of 0.8571, which means that 85.71% of the variation in the percentage of poor people in West Java Province can be explained by the variables used in the model.

Examination of the residual assumptions of the Kolmogorov-Smirnov test yielded a p-value of 0.7405, which is greater than the significance level of 0.05, so that H0 is accepted, indicating that the residuals are normally distributed. This is also supported by the normal Q-Q plot in Figure 5, which shows that the residual points are spread around a straight line. Furthermore, the Breusch-Pagan test yielded a p-value of 0.5483, which is greater than the significance level of 0.05; therefore, H0 is accepted, indicating that there is no spatial heterogeneity. Meanwhile, the results of the Moran index test yielded a p-value of 0.9981, which is greater than the significance level of 0.05; therefore, H0 is accepted, meaning there is no spatial autocorrelation in the residuals.

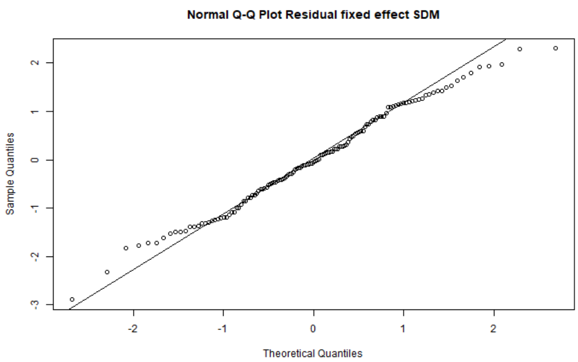


Figure 5: Normal QQ plot of residuals of the SDPM

Interpretation of the spatial panel regression model cannot be explained directly through the estimated values of the resulting parameters because the average change in the percentage of the poor population in a region is not only influenced by a one-unit change in the explanatory variable value in the region itself (direct effect), but is also influenced by changes in the explanatory variables in other regions (indirect effect). Table 6 presents the average magnitude of the impact of each one-unit change in each explanatory variable on the percentage of the poor population generated across all regions.

Table 6: Direct, indirect, and total effects of the SDPM fixed effect model

| Variable | Direct influence | Indirect influence | Total influence |
|---|---|---|---|
| X2 | 0.0178 | 0.0039 | 0.0217 |
| X4 | -0.0058 | -0.0013 | -0.0071 |
| X6 | 1.4590 | 0.3214 | 1.7804 |
| X7 | -0.0013 | -0.0003 | -0.0016 |

The variables percentage of households occupying habitable houses (X2) and average length of schooling (X6) have a positive influence on the rate of people living in poverty in districts/cities in West Java Province. Meanwhile, the variables percentage of people with regional health insurance (X4) and per capita expenditure (X7) have a negative impact on the poverty rate in districts/cities of West Java Province.

The average length of schooling variable (X6) shows a positive coefficient value. This is inversely proportional to the results of data exploration. Data exploration reveals a correlation of -0.69 between the average length of schooling variable and the percentage of the population living in poverty. However, the estimated regression coefficient of the direct, indirect, and total effects exhibit positive values. This may be due to the presence of other variables correlated with the average length of schooling that affect the percentage of the poor population, but are not included in the model (omitted variables), for example, the variable expected length of schooling, so that the regression coefficient estimate is biased (Greene, 2020; Fajri et al., 2023). Another possibility is the selection of inappropriate spatial weights (Vega & Elhorst, 2015).

The direct, indirect, and total effects of the variable percentage of households occupying habitable houses (X2) have positive coefficient values, indicating a positive association with the percentage of the poor population. A 1% increase in households occupying habitable dwellings in a region increases the percentage of the poor population in that region by an average of 0.0178%. Meanwhile, a 1% increase in households occupying habitable houses in an area will increase the percentage of the poor population in neighboring regions by an average of 0.0039%. In total, a 1% increase in the percentage of households occupying habitable houses results in an average 0.0217% increase in the percentage of the poor population in that region. This result does not align with the hypothesis that an increase in the percentage of households occupying habitable houses will decrease the percentage of the population living in poverty. This fact may be due to the possibility that the percentage of the poor population increases because the cost of living is too high to afford habitable houses.

The variable percentage of the population with regional health insurance (X4) shows a negative coefficient value, thus indicating a negative association with the percentage of the poor population. A 1% increase in the population with regional health insurance in a region reduces the percentage of the poor population in that region by an average of 0.0058%. Meanwhile, a 1% increase in the population with regional health insurance in a region reduces the percentage of the poor population in neighboring regions by an average of 0.0013%. In total, a 1% increase in the percentage of the population with regional health insurance reduces the percentage of the poor population in a region by an average of 0.0071%. This finding aligns with research conducted by Situmeang & Hidayat. This result demonstrates that having health insurance can reduce the risk of incurring catastrophic health expenditures, namely expenditures that exceed reasonable limits and have the potential to cause financial stress in households, which can lead to poverty. Having health insurance can provide household economic protection against the burden of medical expenses.

The per capita expenditure variable (X7) exhibits a negative coefficient value, indicating a negative association with the percentage of the population living in poverty. An increase of Rp1,000.00 per person per year in per capita expenditure in a region reduces the rate of the poor population in that region by an average of 0.0013%. Meanwhile, a Rp1,000.00 increase per person per year in per capita expenditure in an area reduces the percentage of the poor population in neighbouring regions by an average of 0.0003%. In total, an increase of Rp1,000.00 per person per year in per capita expenditure reduces the percentage of the poor population in a region by an average of 0.0016%.

### 3.5 Geographically Weighted Panel Regression Modeling

Based on the spatial heterogeneity test, the p-value obtained is less than the significance level of 0.05. According to Table 3, the selected panel regression model is a fixed effects model. Therefore, it is necessary to conduct geographically weighted panel regression (GWPR) modelling using a fixed effects panel model approach. In GWPR, it is necessary to select a spatial weighting matrix calculated using a kernel function. The kernel function is computed using the Euclidean distance between regions, based on geographic coordinate data, specifically latitude and longitude. The best kernel function is selected based on the smallest AIC value and the largest $R^2$. Table 7 presents the results of comparing the GWPR model with six different kernel functions.

Table 7: Results of comparison of kernel weighting functions

| Kernel Weighting Function | AIC | $R^2$ |
|---|---|---|
| *Fixed kernel bisquare* | 88.9071 | 0.7094 |
| ***Fixed Gaussian kernel*** | 42.1780 | 0.8279 |
| *Fixed kernel exponential* | 46.0150 | 0.8194 |
| *Adaptive kernel bisquare* | 78.1694 | 0.7466 |
| *Adaptive Gaussian kernel* | 87.0639 | 0.7131 |
| *Adaptive kernel exponential* | 76.1861 | 0.7424 |

Based on Table 7, the GWPR model with a fixed Gaussian kernel weighting function is the best weighting function because it has the smallest AIC value and the largest $R^2$. The fixed Gaussian kernel weighting function has a minimum CV value of 18.5185 with an optimum bandwidth value of 0.2376. This bandwidth value remains constant for each observation location. Then, GWPR parameters are estimated using the fixed Gaussian kernel weighting function. The parameter estimates in GWPR modelling vary by district/city. Table 8 presents a summary of the estimated parameter values.

Table 8: Summary of estimated values of GWPR model parameters

| Parameter | Minimum | Quartile 1 | Median | Quartile 3 | Maximum |
|---|---|---|---|---|---|
| $\hat{\beta}_0$ | -1.2×10-15 | -6.0×10-16 | -2.9×10-16 | 2.7×10-16 | 7.4×10-16 |
| $\hat{\beta}_{X_1}$ | 0.0363 | 0.0979 | 0.1717 | 0.2188 | 0.3789 |
| $\hat{\beta}_{X_2}$ | -0.0632 | -0.0264 | 0.0004 | 0.0239 | 0.0747 |
| $\hat{\beta}_{X_3}$ | -0.0716 | -0.0188 | 0.0127 | 0.0410 | 0.0677 |
| $\hat{\beta}_{X_4}$ | -0.0208 | -0.0117 | -0.0083 | 0.0008 | 0.0080 |
| $\hat{\beta}_{X_5}$ | -0.0002 | 0.0000002 | 0.000006 | 0.00001 | 0.00004 |
| $\hat{\beta}_{X_6}$ | 0.4628 | 1.2131 | 1.7981 | 3.0817 | 5.3405 |
| $\hat{\beta}_{X_7}$ | -0.0025 | -0.0017 | -0.0008 | -0.000007 | 0.0003 |

After parameter estimation, the next step is to test the parameters of the GWPR model. This test aims to identify explanatory variables that significantly influence the percentage of the population living in poverty in each district/city in West Java Province. Variables with a significant influence have a p-value less than the 0.05 significance level. Table 9 presents the variables that significantly influence the percentage of the population living in poverty in each district/city.

Table 9: Variables with significant influence in each district/city

| Regency/city | Significant Predictors |
|---|---|
| Bogor Regency | X1 |
| Sukabumi Regency | X1, X5 |
| Cianjur Regency | X5, X6, X7 |
| Bandung Regency | X4, X6 |
| Garut Regency | X5, X6, X7 |

| Regency/city | Significant Predictors |
|---|---|
| Tasikmalaya Regency | X6, X7 |
| Ciamis Regency | X5, X6, X7 |
| Kuningan Regency | X6, X7 |
| Cirebon Regency | X6, X7 |
| Majalengka Regency | X1, X6, X7 |
| Sumedang Regency | X4, X5, X6, X7 |
| Indramayu Regency | X1, X6 |
| Subang Regency | X1, X2, X3, X4, X6 |
| Purwakarta Regency | X1, X2, X3, X4, X6 |
| Karawang Regency | X1, X4 |
| Bekasi Regency | X1 |
| West Bandung Regency | X1, X4, X6 |
| Pangandaran Regency | X5, X6, X7 |
| Bogor City | X1 |
| Sukabumi City | X1, X5 |
| Bandung | X1, X4, X6 |
| Cirebon City | X6, X7 |
| Bekasi City | X1 |
| Depok City | X1 |
| Cimahi City | X1, X4, X6 |
| Tasikmalaya City | X6, X7 |
| Banjar City | X5, X6, X7 |

X1: Open Unemployment Rate, X2: Percentage of Households occupying decent housing, X3: Percentage of households with access to decent sanitation, X4: Percentage of population with regional health insurance, X5: Gross regional domestic product, X6: Average Years of Schooling, X7: Per Capita Expenditure

Based on Table 9, the variables that significantly influence each district/city in West Java Province vary. The open unemployment rate variable has a significant influence in urban and industrial areas, such as Bogor Regency, Bekasi Regency, Bekasi City, Bogor City, and Depok City. The average length of schooling variable is the variable that has the most influence on the percentage of poor residents in districts/cities in West Java Province. In addition, the per capita expenditure variable has the most significant influence, along with the average length of schooling variable. Sumedang Regency, Subang Regency, and Purwakarta Regency are areas that face multidimensional challenges because the variables that have significant influences are quite complex. Four variables have a significant influence in Sumedang Regency, namely the percentage of the population with regional health insurance, gross regional domestic product at current prices, average length of schooling, and per capita expenditure. Meanwhile, the percentage of poor people in Subang Regency and Purwakarta Regency is influenced by five of the seven variables used, namely the open unemployment rate, the percentage of households occupying decent housing, the percentage of households with access to proper sanitation, the percentage of the population with regional health insurance, and the average length of schooling. The results of the GWPR model parameter significance test for each district/city in West Java Province form a grouping of districts/cities that share similar variables with significant influence. Figure 6 illustrates a map of the district/city groupings in West Java Province, based on the significant variables impact.

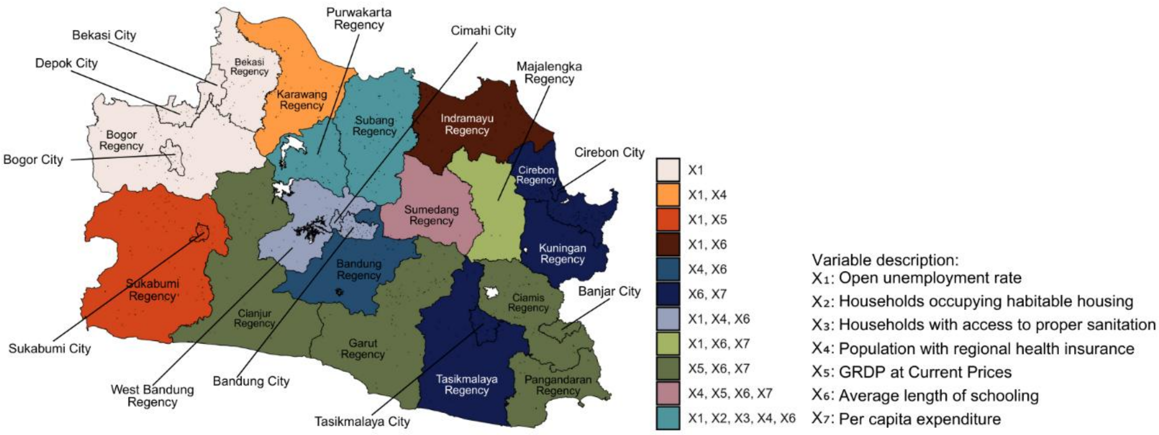


Figure 6: Map of district/city groupings in West Java Province based on the significant predictors

Based on the map in Figure 6, regencies/cities in West Java can be grouped into 11 clusters based on the combination of variables that significantly influence the percentage of the population living in poverty. There is a pattern where adjacent regions tend to have similar combinations of variables. Southern areas, such as Ciamis Regency, Pangandaran Regency, and Banjar City, are grouped together because the same variables influence them. The same combination of variables also influences Garut Regency and Cianjur Regency. Meanwhile, western regions such as Bogor Regency, Bogor City, Depok City, Bekasi City, and Bekasi Regency are characterised by the same variable: the open unemployment rate. Central regions, including Bandung City, Cimahi Regency, and West Bandung Regency, form a separate cluster characterised by a combination of open unemployment rates, the percentage of the population with regional health insurance, and average years of schooling, which reflect urban issues such as unemployment and access to healthcare.

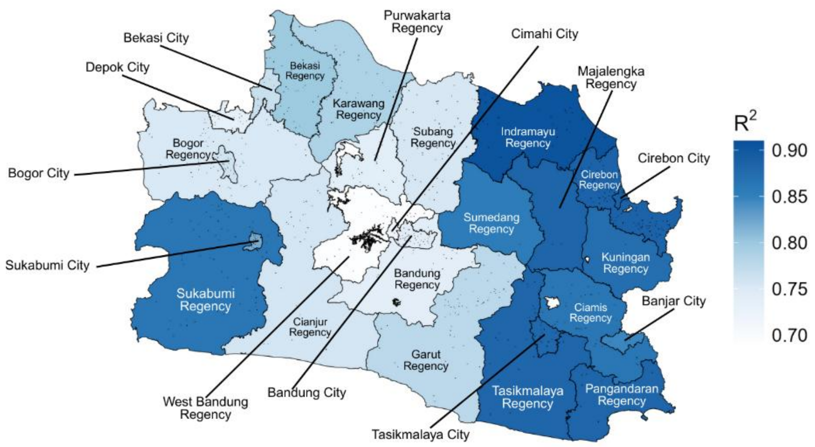


Figure 7: Coefficient of determination (R2) for each district/city

In addition to the significant variables differing across districts/cities, each district/city also has a different coefficient of determination ($R^2$) value (local R2), ranging from 0.6930 to 0.9062. The local R² results for each district/city are presented in Figure 7.

The $R^2$ value illustrates the goodness-of-fit of the GWPR model. The district/city with the lowest local $R^2$ value is West Bandung Regency, with an R² value of 0.6930. This indicates that 69.30% of the variation in the percentage of people living in poverty can be explained by the model, while the remainder is attributed to other factors outside the model. Meanwhile, the district/city with the highest local R-squared value is Indramayu Regency, with an R-squared value of 0.9062. This value indicates that 90.62% of the variation in the percentage of people living in poverty can be attributed to the variables included in the model, while the remaining 9.38% is explained by factors not included in the model. The model formed as many as 27 model equations according to the number of districts/cities in West Java Province. In these model equations, the sign of the regression coefficient for each explanatory variable may differ between the resulting models. The models formed in Garut Regency and Pangandaran Regency are presented in Table 10.

Table 10: GWPR Model of Pangandaran Regency and Garut Regency

| **Regency** | **Model** |
|---|---|
| Garut | $\hat{Y}_{6t} = 3{,}3 \times 10^{-16} + 0{,}1103X1_{6t} - 0{,}0197X2_{6t} + 0{,}0249X3_{6t} - 0{,}0169X4_{6t} + \mathbf{0{,}00003X5^*_{6t}} + 2{,}6976X6^*_{6t} - 0{,}0021X7^*_{6t}$ |
| Pangandaran | $\hat{Y}_{18t} = -6{,}3 \times 10^{-16} + 0{,}0764X1_{18t} - 0{,}0564X2_{18t} + 0{,}0678X3_{18t} + 0{,}0081X4_{18t} - \mathbf{0{,}0002X5^*_{18t}} + 5{,}3405X6^*_{18t} - 0{,}0012X7^*_{18t}$ |

Table 10 shows that the Gross Regional Domestic Product (GRDP) variable at current prices in Garut Regency is positive, while in Pangandaran Regency it is negative. GRDP shows a positive effect on the percentage of the poor population, which is inconsistent with classical economic theory, which assumes that economic growth, as measured by GRDP, should reduce poverty. However, this can be explained through the theory of income distribution and inequality, where an increase in GRDP can lead to higher poverty rates if economic growth is uneven and does not reach the poorest segments of the population (Azizah et al., 2023). In this regard, efforts to reduce the percentage of people living in poverty should be carried out by implementing differentiated approaches between districts/cities through the use of policies tailored to the characteristics of each region.

One area that requires special attention is Tasikmalaya City, which has consistently been recorded as having the highest poverty rate in West Java Province from 2019 to 2023. The following is the GWPR model equation for Tasikmalaya City:

$$\hat{Y}_{26t} = -7{,}2 \times 10^{-16} + 0{,}1188X1_{26t} - 0{,}0046X2_{26t} + 0{,}0037X3_{26t} + 0{,}0014X4_{26t} + 0{,}00001X5_{26t} + 3{,}0817X6^*_{26t} - 0{,}0020X7^*_{26t} \tag{14}$$

The model has an R² of 0.8813, indicating that 88.13% of the variation in the percentage of poor people in Tasikmalaya City can be explained by the variables included in the model; the remaining 11.87% is attributed to variables not considered in the model. The variables that have a significant influence are the average years of schooling (X6) and per capita expenditure (X7). The average years of schooling have a positive effect on the percentage of people living in poverty. Meanwhile, the per capita expenditure variable has a negative impact with a coefficient value of -0.0020, meaning that for Tasikmalaya City in year *t*, if there is an increase of Rp1,000.00/person/year in per capita expenditure, the percentage of poor people will decrease by 0.0020%, assuming other explanatory variables remain constant. This finding aligns with the research of Puteri & Marwan (2023), which indicates that per capita expenditure has a negative and significant impact on poverty in West Sumatra. Increased public spending reflects the population's increasing distance from poverty. Furthermore, it indicates increased accessibility to consumer goods, which can stimulate economic activity. This economic movement has the potential to improve overall public income, thereby reducing poverty levels.

## 4. Conclusion

Based on the results of the spatial effect test, spatial dependency and heterogeneity are indicated. Therefore, spatial panel modeling of SDPM and GWPR can address these issues. The spatial panel model of SDPM that was built is a fixed-effects SDPM model with an R-squared value of 0.8571. In the fixed effect SDPM model, variables that significantly influence poverty are the average length of schooling, per capita expenditure, the percentage of households occupying decent housing, and the percentage of the population with regional health insurance. Meanwhile, the GWPR model, which employs a fixed-effects panel regression model and a fixed Gaussian kernel as the optimal weighting function, yields an $R^2$ value of 0.8279 and generates distinct model equations for each region, with local $R^2$ values ranging from 0.6930 to 0.9062. The explanatory variables that have a significant influence in each region also vary, with the most influential variable being the average length of schooling. Additionally, the open unemployment rate and per capita expenditure also have a significant impact on several regions. Other variables, such as the percentage of households occupying habitable housing, the percentage of households with access to adequate sanitation, the percentage of the population with regional health insurance, and gross regional domestic product at current prices also showed a significant influence, but to a more limited extent.

Future research is expected to incorporate additional explanatory variables, such as expected years of schooling, life expectancy, and labour force participation rates. Furthermore, other spatial weighting matrices, such as spatial contiguity or distance-based measures, can be used for spatial panel modeling.

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