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GEOGRAPHICALLY WEIGHTED REGRESSION WITH DIFFERENT KERNELS: APPLICATION TO MODEL POVERTY

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ABSTRACT

Poverty is still a significant problem in Indonesian development. The poverty alleviation programs implemented have yet to pay attention to spatial aspects, so the policies are often not on target. This study aims to reveal the spatially varying relationships between the poverty level and its factors at the regional scale and compare three fixed kernels as a weighting matrix for GWR. The method used is geographically weighted regression (GWR) with poverty data for 2021. The study results show spatial autocorrelation and is grouped in 29 regencies/cities. The expenditure per Capita, life expectancy, percentage of houses and households with proper drinking water, open unemployment rate, labor force participation rate, and GDP at constant prices show different effects in each region. The results strengthen the argument that spatial aspects cannot be ignored in regional development, especially poverty alleviation. Therefore, area-based poverty alleviation can be used as a basis for determining/determining policies so that they can be more targeted.

1. INTRODUCTION

Poverty is still a problem for all countries, especially developed countries. Sustainable Development Goals (SDGs) launched by the United Nations The nation in 2015 put poverty alleviation (no poverty) as a goal first of its seventeen goals (United Nations General Assembly, 2015). In extreme poverty, people live on less than $1.25 per day. On a national scale, the Government of Indonesia is trying to eradicate poverty extreme to zero percent in 2024. Alleviation efforts for poverty are implemented through special measures through multiple interventions. Such actions are performed with two main approaches: first, reducing the expenditure burden of the group poor and vulnerable through various social protection programs and subsidies. Second, to increase the productivity of the poor and vulnerable groups through economic capacity or income through empowerment. Such efforts are carried out in areas with pockets of poverty, where extreme poverty is common. (The National Team for the Acceleration of Poverty Reduction, 2021).

Referring to the Indonesian Poverty Profile report published by the Central Bureau of Statistics (*Badan Pusat Statistik*/BPS), the percentage of poor people in Indonesia in March 2022 was 26.16 million (9.54 percent of the total population). Of this value, 11.82 million are located in urban areas, and 14.34 million live in rural areas. Another report from BPS, which discloses data on the percentage of poor people according to Provinces and Regions 2021-2022, designates the Bangka Belitung Islands Province with the smallest percentage of poor people is 4.45 percent and Papua Province as the largest with 26.56 percent of people with low incomes. (Central Bureau of Statistics, 2022). In September 2021, the number of poor people in Papua Province was 944.49 thousand and fell to 922.12 thousand in March 2022. Even though it is not a province by population the poorest, East Java, with 4,181.29 thousand poor people, is the province with the highest number, but Papua Province is the largest in percentage terms.

Furthermore, data on the percentage of poor people in Papua Province shows that 5.02 percent live in urban areas, and 35.39 percent live in rural areas. These significant differences can occur because there are regional variations (spatial heterogeneity) and require intervention differs from the policy side. (Central Bureau of Statistics, 2022)

Although there are regional variations, geographic conditions contribute to poverty and are not considered frequently in the research. The location has affected the poverty level because each has different natural, human, and social resources. Spatial poverty occurs in places with lower geographic capital and better physical isolation. (Xu et al., 2019). The study on spatial poverty by Xu (Xu et al., 2019) reveals that the mean slope and road network density had the most statistically significant correlations with the poverty headcount ratio (Xu et al., 2019). Another study found spatial autocorrelation between the number of poor households and the socio-demographic characteristics of low-income families (Nawawi et al., 2019). Conversely, Azzarri's study shows that living in more humid areas positively correlates with welfare (Azzarri & Signorelli, 2020). Salvacion's study used Geographically Weighted Regression (GWR) to determine patterns and factor affection poverty in the Philippines and found that several variables' impacts vary among villages (Salvacion, 2020).

The concept of space has been further introduced into the study of poverty with the growing awareness of the non-volatility of spatial features. Spatial theories of poverty have evolved to study the spatial distribution of poverty and its relationship to the geographic environment and resource endowments. (Kam et al., 2005). Papua is a largely undeveloped forest area that has long been managed as a national frontier for resource extraction (Sloan et al., 2019). Papua province is located in the easternmost of Indonesia, directly adjacent to Papua New Guinea. The province covered approximately 312,224 km^2 and became the home of 4.303,707 residents in 2020. The province is administratively split into 28 regencies and one city. In addition to the Papua mainland, there are 600 islands as part of the Papua region. The altitude ranged from 4.79 to 2,303 m.a.s.l. (Central Bureau of Statistics, 2021)

The study aims are:

1. To reveal the spatially varying relationships between the poverty level and its factors in Papua province at the regional scale using Geographically Weighted Regression (GWR); and

2. Comparing three fixed kernels as a weighting matrix for GWR.

2. METHODS

2.1. Data

The data used in this study is the 2021 National Socioeconomic Survey data published by BPS. The data contains Indonesian household welfare. The independent variables used are the Average Length of School (RLS) for people aged ≥ 15 years (X1), RLS for people aged ≥ 25 years (X2), Expenditure per Capita (X3), Human Development Index (X4), Life expectancy (X5), Percentage of Households with Proper Sanitation (X6), Percentage of Houses Households with Proper Drinking Water (X7), Open Unemployment Rate (X8), Labor Force Participation Rate (X9), and GDP at constant Prices (X10). The Percentage of Poor People (Y) is the dependent variable in this study.

2.2. Linear Regression Analysis

Linear regression analysis is a method used to express the relationship between a dependent or response variable (Y) with several independent variables or predictors (X). Multiple linear regression models for k predictor variables and n number of observations can be written:

$$\boldsymbol{Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{pi} + \varepsilon_i, i = 1, 2, \ldots, n}$$

Where:

$\boldsymbol{Y_i}$	= Response variable to the i-th Observation
$\boldsymbol{\beta_0, \beta_1, \ldots, \beta_p}$	= Unknown parameters
$\boldsymbol{X_{1i}, X_{2i}, \ldots, X_{pi}}$	= Predictor variable
$\boldsymbol{\varepsilon_i}$	= *Error* for i-th Observation

Estimating the regression model parameters generally uses the Ordinary Least Square (OLS) method, which minimizes the number of squared errors.

2.3. Spatial Dependence

Spatial data has characteristics, namely spatial dependencies and spatial diversity. One way to determine the existence of spatial dependencies between locations is to perform spatial autocorrelation tests using Moran's index statistics (Chen, 2013). The spatial dependency measurement tool is by using the Moran Index with the following formula:

$$\boldsymbol{Z = \frac{I - E(I)}{\sqrt{Var(I)}}}$$

Where:

$\boldsymbol{Z}$ = Moran's index statistics test's value

$\boldsymbol{I}$ = Moran's index value

2.4. Geographically Weighted Regression

Geographically Weighted Regression (GWR) is a development of linear regression in which the GWR applies locally. This model calculates parameters at each observation location, so each location will have a different regression model (Mahdy, 2020). The model form of the GWR is as follows:

$$\boldsymbol{y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i}$$

Where:

$\boldsymbol{y_i}$ = Dependent variable in i-th location $i(i = 1, 2, \ldots, n)$

$\boldsymbol{x_{ik}}$ = Independent variable k-th in i-th location $i(i = 1, 2, \ldots, n)$

$(\boldsymbol{u_i, v_i})$ = Longitude, Latitude for i-th point in a certain location

$\boldsymbol{\beta_k}(\boldsymbol{u_i, v_i})$ = k-th regression coefficient for each location

$\boldsymbol{\varepsilon_i}$ = *Error* which assumed identic, independent, and normally distributed with zero mean and constant variance $\boldsymbol{\sigma^2}$

With the weighted least squares (WLS) method, the parameter Estimator at the i-th location is formulated as:

$$\boldsymbol{\widehat{\beta}_i = (X'W(i)X)^{-1}X'W(i)y}$$

With $W(i) = diag[w_1(i), w_2(i), \ldots, w_n(i)$. $W(i)$ Is a diagonal matrix with $n \times n$ size, which is the i-th spatial weighting matrix whose diagonal elements are determined by the proximity of the i-th location to other locations.

2.5. Weighting Matrix

The weighting matrix (W) is based on the neighbors' distance or the distance between each Observation. Greater weight is given to the closest observation point to the regression point. The kernel function is one of the weighting methods for GWR. This function estimates parameters in the GWR if the distance function is a continuous and monotonical descending function. The weights formed using this kernel function are the Gaussian Distance Function, the Bisquare function, and the Tricube kernel function. (Ardianti et al., 2021; Fotheringham et al., 2003; Putra et al., 2022; Yasin, 2011)

Below are the formulas for the fixed kernel.

a. **Fixed Gaussian Kernel:**

$$\boldsymbol{W_j(u_i, v_i) = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right]}$$

b. **Fixed Bisquare Kernel:**

$\boldsymbol{W_j(u_i, v_i) = \left[1 - \left(\frac{d_{ij}}{h}\right)^2\right]^2}$, if $d_{ij} < h$, and $W_j(u_i, v_i) = 0$ for $d_{ij} \geq h$.

c. **Fixed Tricube Kernel:**

$\boldsymbol{W_j(u_i, v_i) = \left[1 - \left(\frac{d_{ij}}{h}\right)^3\right]^3}$, if $d_{ij} < h$, and $W_j(u_i, v_i) = 0$ for $d_{ij} \geq h$.

2.6. Optimum Bandwith

Bandwidth selection will affect the accuracy of the estimation results and thus became important. One of the methods for bandwidth selection is Cross Validation (CV) at all locations, with the formula (Putra et al., 2022):

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

Where:

$\boldsymbol{y_i}$	= Observation's value of i-th response variable
$\boldsymbol{\hat{y}_{\neq i}(h)}$	= Estimator where the Observation at location i-th is omitted from the estimation process

In cases where the bandwidth is unknown or there is no prior justification for supplying a particular bandwidth, the researcher can use software to choose an appropriate bandwidth. Two methods are available in the software to accomplish this. Cross-validation is a technique in which the optimal bandwidth minimizes the score. (Fotheringham et al., 2003)

2.7. Data Analysis

For data analysis, a multicollinearity test will determine whether a linear relationship exists between independent variables in models. Then global regression performs for the independent variables, which contain no multicollinearity between each. The spatial dependence test is then applied to determine the existence of spatial dependencies between locations.

3. RESULTS AND DISCUSSION

3.1. Results

The data used in this study are based on the number of regencies and cities in Papua Province, namely 28 regencies and one city. The followings are the variables or indicators measured in each regency/city.

Table 1 Data definition

Variable's Name	Description
Y	Percentage of poor people in Papua Province (percent)
X1	The average length of schooling for the population is over 15 years (years)
X2	The average length of schooling for the population is over 25 years (years)
X3	Expenditure per Capita (thousands/person/year)
X4	Human Development Index
X5	Life expectancy (years)
X6	Percentage of households with proper sanitation (percent)
X7	Percentage of houses households with proper drinking water (percent)
X8	Open unemployment rate (percent)
X9	Labor force participation rate (percent)
X10	Gross Domestic Product (GDP) at constant prices (Indonesian's Rupiah/IDR)

Table 1 shows one dependent and ten independent variables from BPS 2021 National Socioeconomics Survey data.

3.1.1. *Descriptive Statistics*

Simple descriptive statistics can be seen from each variable's minimum, maximum, average, and standard deviation values with the aim of data exploration. Here are simple descriptive statistics.

Table 2 Simple descriptive statistics

Variable	Minimum	Median	Maximum	Average	Std. Deviation
Y	10.16	29.85	41.66	28.38	9.73
X1	1.42	5.60	11.57	6.25	3.03
X2	1.92	6.69	11.39	6.78	2.67
X3	3,976	5,736	14,937	6,820	2,545
X4	32.84	56.70	80.11	57.70	11.10
X5	55.43	65.86	72.36	65.26	3.67
X6	0.00	31.34	85.73	40.29	34.07
X7	0.00	72.89	98.67	63.87	29.39
X8	0.00	2.19	11.67	3.22	3.08
X9	56.39	78.20	97.93	78.40	11.94
X10	767,101	1,556,231	69,619,313	5,540,775	1,315,230

The average percentage of poor people in Papua Province (Y) is 28.38 (in thousands), with a 9.73 standard deviation. The most significant percentage of poor people can be found in the Intan Jaya regency, with 41.66 percent of its residents classified as poor. On the other hand, Merauke regency, with 10.16 percent poor, is the least suffering region in terms of poverty. Gross Domestic Product at a constant price, variable X10, ranged from 767,101 to 69,619,313, with 1,556,231 as the median value. The Intan Jaya regency is also an impoverished regency with the smallest GDP. The foremost GDP is held by Mimika, the home of the most considerable mining activity in Papua.

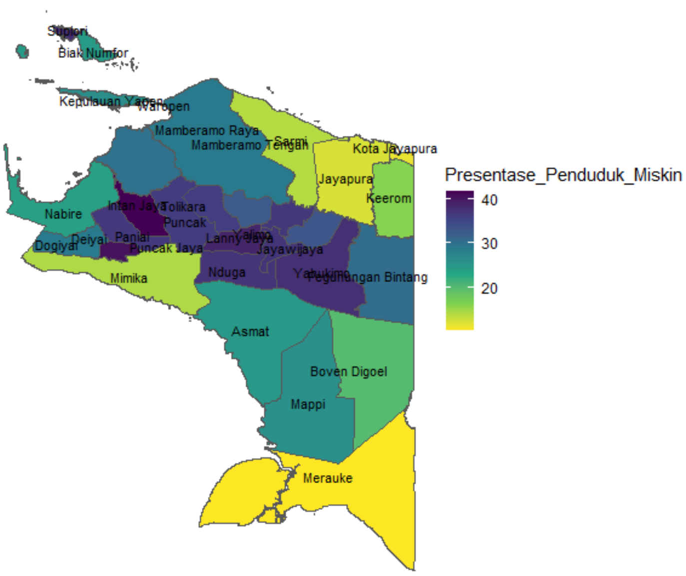

Figure 1 Percentage of Poor People in Papua Province

The previous figure shows the percentage of poor people in Papua Province suchMerauke regency, Jayapura city, Keerom regency, Sarmi regency, and Mimika regency, as the regencies with lesser percentages.

3.1.2. *Multicollinearity Test*

The multicollinearity assumption test is performed before the regression analysis to determine whether there is a linear relationship between independent variables in models. If the independent variable is indicated to contain multicollinearity, it will cause a large residual in parameter estimation results. This study considers the value of VIF (Variance Inflation Factors) to test the multicollinearity assumption. VIF values less than ten (VIF <10) imply that the related independent variables do not contain multicollinearity. Below is the independent variable list, along with the VIF value.

Table 3 VIF Value for each independent variable

Variable's Name	Description	VIF
X1	The average length of schooling for the population is over 15 years (years)	71.52
X2	The average length of schooling for the population is over 25 years (years)	16.11
X3	Expenditure per Capita (thousands/person/year)	9.84
X4	Human Development Index	52.96
X5	Life expectancy (years)	3.12
X6	Percentage of households with proper sanitation (percent)	15.29
X7	Percentage of houses households with proper drinking water (percent)	1.58
X8	Open unemployment rate (percent)	2.89
X9	Labor force participation rate (percent)	4.57
X10	Gross Domestic Product (GDP) at constant prices (Indonesian's Rupiah/IDR)	1.96

Table 3 shows several independent variables have VIF values greater than ten (X1, X2, X4, X6). Those variables are suspected of containing multicollinearity and, as a result, will be removed. Multicollinearity indicates a high degree of linear intercorrelation between independent variables in a multiple regression that causes incorrect regression analysis results. There are three diagnostic tools of multicollinearity, i.e., variance inflation factor (VIF), condition index and condition number, and variance decomposition proportion (VDP) (Kim, 2019). Following the previous step, the VIF values for the independent variables indicated no multicollinearity.

Table 4 VIF Value for each independent variable (follow-through)

Variable's Name	Description	VIF
X3	Expenditure per Capita (thousands/person/year)	3.46
X5	Life expectancy (years)	1.54
X7	Percentage of houses households with proper drinking water (percent)	1.49
X8	Open unemployment rate (percent)	2.45
X9	Labor force participation rate (percent)	1.98
X10	Gross Domestic Product (GDP) at constant prices (Indonesian's Rupiah/IDR)	1.77

The last table shows all variables have VIF values less than ten which implies no multicollinearity between each variable. The following analytical procedures will use the last six independent variables.

3.1.3. *Global Regression*

Significantly test partially determines the effect of each independent variable on the dependent variable. The null hypothesis of this test is that there is no significant influence partially between the independent and dependent variables.

Table 5 Linear regression model

Variable	Estimate	Std. Error	t value	Significance
(Intercept)	8.845	0.2847	0.311	0.75894
X3	-0.002826	0.0008489	-3.329	0.00305
X5	0.4093	0.3920	1.044	0.30771
X7	-0.03848	0.04829	-0.797	0.43397
X8	0.2589	0.5903	0.439	0.66525
X9	0.1758	0.1370	1.284	0.21265
X10	0.00000001	0.0000001	-0.102	0.91957

F-statistics: 8.021 on 6 and 22 DF, p-value: 0.000, R-squared: 0.6863, Adjusted R-squared: 0.6007.

According to Table 5, we can create the linear regression model below.

$$\boldsymbol{Y = 8.84 - 0.002826X_3 + 0.4093X_5 - 0.03848X_7 + 0.2589X_8 + 0.1758X_9 + 0.0000000X_{10}}$$

The results show large F-statistics and p-value less than 0.05, meaning variables X3, X5, X7, X8, X9, and X10 are simultaneously significant to the dependent variable. Furthermore, variable X3 (Expenditure per Capita) has t-value probabilities less than 0.05, which implies that the variable is partially significant to the dependent value.

3.1.4. *Spatial Dependence Test*

To determine the existence of spatial dependencies between locations, Moran's index statistics were used. The test has a p-value of 0.001, which means significant to $\alpha = 5\%$. Based on Moran's index statistics results, we can conclude that there is spatial dependence on the data.

3.1.5. *GWR Model with Fixed Gaussian Kernel*

Optimum bandwidth obtained by minimizing Cross Validation (CV) value. Using a fixed gaussian kernel, the CV values are below.

Table 6 Optimum bandwidth using fixed gaussian kernel

Bandwidth	CV
3.344465	1430.091
5.406056	1569.995
2.070332	1389.014
1.197955	5494.148
2.557008	1340.758
2.610792	1345.403
2.458097	1334.559
2.309984	1334.738
2.386375	1332.821
2.380938	1332.819
2.353836	1332.813
2.381519	1333.082
2.38156	1332.813
2.381478	1332.813
2.381519	1332.813

From Table 6, the optimum bandwidth is 2.381519 with a minimum CV value of 1332.813. The outcomes of GWR are significantly impacted by bandwidth selection. The bandwidth is a smoothing parameter, with more significant bandwidths leading to smoother results. An under-smoothed model will provide parameters with a great deal of local variance, making it challenging to identify any patterns. In contrast, an over-smoothed model will produce parameters with values that are comparable across the research area. The "best" bandwidth compromises these two options (Fotheringham et al., 2003). That is why the decision to choose 2.381519 as an optimum bandwidth, even though there are two other bandwidths with the same CV.

GWR modeling uses a weighting matrix for each location based on the optimal bandwidth. The results of the GWR modeling are as follows.

Table 7 GWR Model with a fixed Gaussian kernel

Variable	Minimum	Median	Maximum	R-Square
Intercept	10.437	13.926	24.934	
X3	-0.0035031	-0.002917	-0.0021236	
X5	-0.051572	0.30422	0.47722	79.24%
X7	-0.066137	-0.038936	-0.018760	
X8	-0.47133	-0.024667	0.40159	
X9	0.085111	0.18130	0.28336	
X10	-0.00000009	-0.00000002	0.00000009	

GWR model with fixed gaussian kernel results shows that Expenditure per Capita, Life expectancy, Percentage of houses and households with proper drinking water, open unemployment rate, and GDP at constant prices have negative correlations with the percentage of poor people in Papua Province, which means that the increase in these variables will lower the percentage of poor people.

3.1.6. *GWR Model with Fixed Bisquare Kernel*

Optimum bandwidth obtained by minimizing Cross Validation (CV) value. Using a fixed bisquare kernel, the CV values are below.

Table 8 Optimum bandwidth using fixed bisquare kernel

Bandwidth	CV
3.344465	NA
5.406056	1546.684
5.406015	1546.721
5.406096	1546.648
6.680214	1354.71
6.17348	1333.511
6.343452	1337.011
6.095238	1334.366
6.177379	1333.516
6.171001	1333.51
6.170635	1333.51
6.170676	1333.51
6.170594	1333.51
6.170635	1333.51

From Table 8, the optimum bandwidth is 6.170635 with a minimum CV value of 1333.51. GWR modeling uses a weighting matrix for each location based on the optimal bandwidth. The results of the GWR modeling are as follows.

Table 9 GWR model with fixed bisquare kernel

Variable	Minimum	Median	Maksimum	R-Square
Intercept	10.706	13.131	23.324	77.29%
X3	-0.0033774	-0.0022998	-0.0020719	
X5	0.0089896	0.30949	0.42953	
X7	-0.062873	-0.037157	-0.025632	
X8	-0.44645	-0.019826	0.32668	
X9	0.091693	0.16946	0.27220	
X10	-0.0000001	0.00000002	0.00000009	

GWR model with fixed bisquare kernel results shows expenditure per Capita, Percentage of houses and households with proper drinking water, open unemployment rate, and GDP at constant prices have negative correlations with the percentage of poor people in Papua Province. In comparison, life expectancy and labor force participation rate have positive correlations for the dependent variable.

3.1.7. *GWR Model with Fixed Tricube Kernel*

Optimum bandwidth obtained by minimizing Cross Validation (CV) value. Using a fixed tricube kernel, the CV values are below.

Table 10 Optimum bandwidth using fixed tricube kernel

Bandwidth	CV
3.344465	NA
5.406056	1846.503
5.406015	1846.574
5.406096	1846.433
6.680214	1338.65
6.234416	1335.513
6.450127	1330.072
6.432215	1329.898
6.413646	1329.815
6.407694	1329.811
6.408353	1329.811
6.40841	1329.811
6.40845	1329.811
6.40841	1329.811

From table 10, the optimum bandwidth is 6.40841 with a minimum CV value of 1329.811. GWR modeling uses a weighting matrix for each location based on the optimal bandwidth. The results of the GWR modeling are as follows.

Table 11 GWR Model with fixed tricube kernel

Variable	Minimum	Median	Maximum	R-Square
Intercept	10.553	12.483	22.100	75.38%
X3	-0.0032257	-0.023283	-0.0020098	
X5	0.059605	0.24848	0.41375	
X7	-0.060308	-0.044321	-0.030021	
X8	-0.38040	-0.16516	0.26609	
X9	0.097556	0.13734	0.28550	
X10	-0.0000001	-0.00000006	0.00000008	

GWR model with fixed tricube kernel results shows expenditure per Capita, Percentage of houses and households with proper drinking water, open unemployment rate, and GDP at constant prices have negative correlations with the percentage of poor people in Papua Province. In contrast, life expectancy and labor force participation rate have positive correlations for the dependent variable. The previous statement implies that the first four variables contribute negatively to the poor people percentage while the life expectancy variable and labor force participation rate variable do the opposite.

3.2. Discussion

Before incorporating spatial dependencies, this study used six variables on Global regression (Table 5). Expenditure per Capita, Life expectancy, percentage of houses and households with proper drinking water, Open unemployment rate, Labor force participation rate, and GDP at constant prices. Although all independents variable is simultaneously significant to the dependent variable, Expenditure per Capita is found to be partially significant to the percentage of poor people in Papua Province. The finding that Expenditure per Capita is partially significant to the percentage of poor people differs from Dahliah's study (Dahliah & Nirwana Nur, 2021), which found that GDP is significant to the poverty level in East Luwu. Latif's (Latif et al., 2019) study on factors determining poverty and child mortality in Pakistan found that the Consumer price index, GDP, Number of Hospitals, and Unemployment rate are significant to the percentage of the population below the poverty line.

Calculation of Moran's index indicating spatial dependencies on the data used in this study. Our results are in line with previous studies, such as Harrison’s (Harrison et al., 2019), David’s (David et al., 2018), Azzari’s (Azzarri & Signorelli, 2020), Dong’s (Dong et al., 2021), Rinaldi’s (Rinaldi et al., 2021; Silva et al., 2022), and Silva’s (Silva et al., 2022) which also found spatial dependencies in their studies. Geographically weighted regression with Fixed Gaussian Kernel has a better result with determination coefficients of 79.24%. The results agree with Ardianti’s study (Ardianti et al., 2021), which found that GWR with a Fixed Gaussian Kernel model provides a better model. Another study by Nurpadilan (Nurpadilah et al., 2021) found that the GWR model with a fixed exponential kernel gives the best model rather than another fixed and adaptive kernel.

The local model from the GWR with Fixed Gaussian Kernel is presented below.

Table 12 Local model for each regency and city

No	Regency/City	Intercept	β_3	β_5	β_7	β_8	β_9	β_{10}	R^2
1	Merauke	15,99167423	-0,00350314	0,29576528	-0,05057461	0,25904967	0,21657636	9,1371E-08	0,84927545
2	Jayawijaya	15,79499549	-0,00228647	0,19869863	-0,04499173	0,04291167	0,22047847	8,0468E-09	0,76504357
3	Jayapura	21,41827305	-0,00218148	0,05628601	-0,05679866	0,25731614	0,25095482	4,2941E-08	0,7606841
4	Nabire	12,2242648	-0,00228342	0,44040828	-0,02094638	-0,39739191	0,094141	-8,7223E-08	0,74791198
5	Kepulauan Yapen	13,30702091	-0,00229332	0,40688854	-0,03333843	-0,09521699	0,10651736	-8,6105E-08	0,72317308
6	Biak Numfor	12,39908996	-0,00234869	0,44534385	-0,0389358	-0,02466668	0,0949263	-9,3297E-08	0,71543508
7	Paniai	11,94379538	-0,00229173	0,39866639	-0,02473674	-0,31208125	0,12551928	-6,7337E-08	0,7512347
8	Puncak Jaya	12,13212451	-0,00231294	0,36684927	-0,02768106	-0,24652894	0,14613986	-5,2442E-08	0,75481304
9	Mimika	10,43740657	-0,00237301	0,42213662	-0,02274054	-0,36056467	0,12995691	-5,9621E-08	0,7632837
10	Boven Digoel	13,92559723	-0,00273512	0,22724765	-0,05516814	0,18383435	0,24663047	6,1068E-08	0,80576562
11	Mappi	12,61706407	-0,00298893	0,28724876	-0,04599697	0,15070329	0,23139456	5,4993E-08	0,8175841
12	Asmat	11,06284338	-0,0025835	0,31186866	-0,03615458	-0,04666003	0,2093912	5,5453E-09	0,7857649
13	Yahukimo	15,64239138	-0,00231393	0,17423744	-0,05040317	0,09714651	0,24109149	2,8989E-08	0,77374425
14	Pegunungan Bintang	16,69360485	-0,00228012	0,12194879	-0,0595211	0,18444402	0,26491341	5,747E-08	0,77858306
15	Tolikara	13,95929151	-0,00226566	0,3287819	-0,03140493	-0,15723319	0,14979064	-5,1655E-08	0,74570279
16	Sarmi	20,60489996	-0,00224619	0,13600124	-0,04950637	0,20478981	0,20777769	3,4723E-09	0,74897946
17	Keerom	21,55226726	-0,0021352	0,00951827	-0,06400886	0,3035251	0,2802192	7,5696E-08	0,76749556
18	Waropen	14,85187569	-0,00228784	0,34845628	-0,03679166	-0,01671898	0,12827828	-6,8095E-08	0,72720414
19	Supiori	11,65949002	-0,002385	0,47721907	-0,04160029	-0,01303526	0,08511066	-9,9446E-08	0,71223268
20	Mamberamo Raya	16,54755892	-0,0022749	0,28258908	-0,03908046	0,02904176	0,15351512	-4,6643E-08	0,7353961
21	Nduga	12,67975733	-0,00236582	0,30422195	-0,03424204	-0,11747829	0,18576904	-2,1159E-08	0,76480319
22	Lanny Jaya	14,55952045	-0,0022939	0,26660402	-0,03716825	-0,06620736	0,18733853	-2,1011E-08	0,75724864
23	Mamberamo Tengah	18,37880635	-0,00226286	0,2115508	-0,04340837	0,10191859	0,18129958	-2,2111E-08	0,7432781
24	Yalimo	15,11110318	-0,0022856	0,247158	-0,03905232	-0,0347657	0,194256	-1,5176E-08	0,75776915
25	Puncak	13,48799793	-0,00227865	0,33322579	-0,03079932	-0,17606661	0,1525646	-4,91E-08	0,74922136
26	Dogiyai	11,52392842	-0,00232005	0,45792239	-0,01876022	-0,47133341	0,09159679	-8,3892E-08	0,75703553
27	Intan Jaya	12,929122	-0,00226162	0,37997227	-0,0269384	-0,2502721	0,12603111	-6,9436E-08	0,74350925
28	Deiyai	11,57234761	-0,00229992	0,43454042	-0,02125551	-0,40040358	0,10574783	-7,8376E-08	0,75329147
29	Jayapura City	24,93392102	-0,00212358	-0,05157151	-0,06613704	0,401592	0,28336451	8,529E-08	0,7621867

Each regency or city has a different model; for example, the Jayapura City model can be formulated below:

$$\begin{aligned} \boldsymbol{Y_{Jayapura\ City}} = \mathbf{24.93392102} - \mathbf{0.00212358}\boldsymbol{X_3} - \mathbf{0.05157151}\boldsymbol{X_5} \\ - \mathbf{0.06613704}\boldsymbol{X_7} + \mathbf{0.401592}\boldsymbol{X_8} + \mathbf{0.28336451}\boldsymbol{X_9} \\ + \mathbf{0.00000008}\boldsymbol{X_{10}} \end{aligned}$$

The local model for Jayapura City has a determination coefficient (R2) of 76.21%, meaning that the model can explain the percentage of poor people in the area. In comparison, the rest (23.79%) will be explained by other variables not included in the study.

4. CONCLUSION

Based on the estimation results of GWR spatially, the expenditure per Capita, life expectancy, percentage of houses and households with proper drinking water, open unemployment rate, labor force participation rate, and GDP at constant prices show different effects in each region. This indicates that there is a spatial influence on the percentage of poverty. These results strengthen the argument that spatial aspects cannot be ignored in regional development, especially poverty alleviation. Therefore, area-based poverty alleviation can be used as a basis for determining/determining policies so that they can be more targeted. This can be done through the synergy of poverty alleviation policies and programs so that activities do not overlap in the exact location. Furthermore, our study found that applying a Fixed Gaussian Kernel on the GWR model gave a better result than Fixed Bisquare Kernel and Fixed Tricube Kernel. GWR model with Fixed Gaussian Kernel with the optimum bandwidth 6.170635 and CV value of 1333.51 give determination coefficients (R^2) 77.29%.

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