EKO-REGIONAL: JURNAL PEMBANGUNAN EKONOMI WILAYAH
Volume 18, Issue 2, September 2023, pp. 194 – 209
http://jp.feb.unsoed.ac.id/index.php/eko-regional/article/view/3566
DOI: https://doi.org/10.32424/1.erjpe.2023.18.2.3566

Comparing Spatial Welfare Among Major Cities in Java

By
Firdha Kusuma Wardani, Evi Gravitiani [*)], Tetuko Rawidyo Putro
Faculty of Economics, Sebelas Maret University, Surakarta
[*)]Corresponding Author : evigravitani_fe@staff.uns.ac.id

Submission: June 18, 2023; Accepted: September 26, 2023

ABSTRACT: Education, economy, health, tourism, industry, transportation, and social welfare were significantly affected by the 2021 COVID-19 pandemic. The benchmark for welfare is properly fulfilling the basic needs of society. This study aims to model the level of social welfare in big cities on the island of Java in 2021 by including spatial effects. The method used is Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR). GWR model, the weighting used is the Gaussian kernel function. The OLS model produces an R^2 of 83.96%, while the GWR model produces an R^2 of 84.03%. This shows that the GWR model is better at explaining the level of diversity in the welfare of cities on the island of Java, which is 84.03%, and the rest is influenced by geographical factors because there is no significant difference between the linear regression model and GWR.

Keywords: Welfare, Geographically Weighted Regression, Ordinary Least Square, Life Expectancy, Spatial.

ABSTRAK: *Pendidikan, ekonomi, kesehatan, pariwisata, industri, transportasi, dan kesejahteraan sosial sangat terpengaruh oleh Pandemi Covid-19 tahun 2021. Tolak ukur kesejahteraan adalah dapat terpenuhinya kebutuhan dasar masyrakat secara layak. Penelitian ini bertujuan untuk memodelkan tingkat kesejahteraan masyarakat kota-kota besar di pulau jawa tahun 2021 dengan memasukan efek spasial. Metode yang digunakan adalah Ordinary Last Square dan Geographically Weighted Regression. Dalam model GWR pembobotan yang digunakan adalah fungsi karnel gaussian. Model OLS menghasilkan* R^2 *sebesar 83,96% sedangkan model GWR menghasilkan* R^2 *Sebesar 84,03%. Hal tersebut menujukan tingkat keragaman kesejahteraan kota-kota di pulau jawa sebesar 84,03% dan sisanya dipengaruhi oleh faktor geografis karena tidak ada perbedaan signifikan antara model regresi linier dan GWR.*

Kata Kunci: *Kesejahteraan, Geographically Weighted Regression, Ordinary Least Square, Harapan Hidup, Spasial.*

INTRODUCTION

National development is the essence of improving people's welfare (Karyono et al., 2021). Household prosperity can be an indicator of their standard of living. A higher standard of living shows that a family is doing well, and a prosperous family has the resources to improve their standard of living (Reskia, 2022). Early post-war "classic" development economists generally believed that income was a good proxy for social well-being. This viewpoint is based on the principles of neoclassical economics, which argues that the welfare or utility of individuals is a function of the products and services they consume and that as their income increases, their consumption will also increase. (Case & Fair, 2003).

The current development paradigm is economic growth measured by human development (Kadri et al., 2020). The Human Development Index (HDI) was first introduced by UNDP in 1990 through the Human Development Report (HDR) (Putri et al., 2022). According to UNDP, HDI is an important indicator to measure success in efforts to shape the quality of human life because it is able to explain how the population can access development results to obtain income, health, and education (Sadarrudin et al., 2022). Therefore, HDI has a big contribution to the status of human development in a region and is very useful, especially for the government as a benchmark or reference for development planning and allocation of funds to improve welfare (Karyono et al., 2022). The status of community welfare can be measured based on the Human Development Index (HDI) or Human Development Index (HDI) (Central Bureau of Statistics, 2021).

In 2021, the COVID-19 pandemic has had a huge impact on the development of life sectors, such as education, economy, health, tourism, industry, transportation, and especially social welfare (Mursito et al., 2022)Welfare conditions during the Pandemic experienced a significant deterioration, seen from the restricted social side, then the disruption of each person's mental health due to excessive anxiety and stress due to fear of contracting the virus, whether or not their daily primary needs were met and fear of uneven social assistance provided by the government (Central Bureau of Statistics, 2021). Law Number 11 of 2009 explains that Welfare is a condition of fulfilling the material, spiritual and social needs of citizens in order to live properly and be able to develop themselves so that they can carry out their social functions (Murni et al., 2018)

However, it should be noted that the impact of the COVID-19 pandemic on public health and socioeconomic conditions seriously affects people's Psychological well-being (Yamada & Shimizutani, 2022)In fact, the use of various control measures such as social distancing and remote working has drastically changed the way many people work, not only that, stricter protective measures, such as the closure of non-essential work activities, have also forced many workers to remain inactive at home (Riccardi et al., 2023). From a social perspective, this pandemic has made individuals unable to have physical contact, keep their distance and always wear a mask (Kartika & Kholijah, 2020). It is no surprise that along with the COVID-19 pandemic, lockdown measures and social distancing triggered a more hidden parallel pandemic, namely community-wide mental health disorders (Chakraverty & Gupta, 2022). Thus, social welfare requires the role of the community, both from individuals, families, religious organizations, community social organizations, charities, social welfare institutions and foreign social welfare institutions, for the implementation of integrated, directed and sustainable social welfare (Fahrudin, 2012; Giacalone et al., 2022).

Of course, the COVID-19 phenomenon causes a decrease in community welfare which will impact the poverty rate, the number of unemployed, and the GRDP and other economic sectors (Arthayanti et al., 2017). Poverty and unemployment rates reflect the welfare status of the community in a particular area (Shintia & Yasin, 2015). According to the Regional Planning and Development Agency (BAPPEDA), a welfare indicator that also shows the high level of welfare in a country or region is the employment indicator, which is reflected in the decline in the open unemployment rate (TPT (Maulana et al., 2019).

The Human Development Index (HDI) is an indicator issued by the UNDP to measure the progress made in human development and well-being (Sarabhai, 1975). The first Human Development Report published by UNDP in 1990 incorporated the capabilities approach proposed by Amartya Sen, focusing on meeting basic needs aimed at helping the most disadvantaged (Martínez et al., 2019). The Human Development Index (HDI) measures a country's prosperity by considering three factors: longevity, education level, and income level (Central Bureau of Statistics, 2021). This report creates the Human Development Index (HDI), which represents the median of the normalized indices for the three main aspects of good health and longevity, level of knowledge, and decent standard of living, as stated in the 2021 UNDP report(Qiu et al., 2018). To measure health, life expectancy at birth is used as an indicator. At the same time, the education aspect is evaluated by considering the expected years of schooling for children just starting education and the average number of years spent by adults aged 25 in education. Gross national income per individual measures the standard of living dimension (Djokoto & Wongnaa, 2023).

The level of welfare is an important parameter in measuring the quality of life of a population. Various factors can contribute to the level of welfare. Among these factors, some play a key role in determining the quality of life of individuals and society as a whole. Life expectancy is one such factor that significantly influences a society's level of well-being (Collins, 2017). The main reason behind this is that Life Expectancy reflects the estimated years of life that individuals can enjoy in a healthy and productive condition. In other words, the higher the Life Expectancy Rate, the longer people in a society can live a healthy life, contribute to the economy, and actively participate in various aspects of life (Cui & Chang, 2020).In addition to Life Expectancy, the level of education is also a key factor in determining the level of well-being of a society. This is due to several very significant reasons. First, education provides individuals with the necessary knowledge and skills to enter the job market with better opportunities. With a high level of education, an individual is more likely to get a better job and earn a higher income, which directly contributes to personal and family economic well-being (Freire et al., 2018)

Furthermore, liveability standards also play an important role in improving welfare levels. This includes decent housing, access to clean water, adequate sanitation, and other basic infrastructure. A high standard of living creates a favourable environment for people's physical and mental well-being. In addition, the percentage of poor people and the unemployment rate also significantly impact welfare (Borjas, 2016). High levels of poverty indicate economic inequality that can reduce overall well-being, while high levels of unemployment result in a lack of access to employment and income, which directly affects the quality of life of individuals (J. Wang et al., 2021).

Java is one of the islands in Indonesia that has the highest population density in Indonesia (Hartanto et al., 2019). The large number of cities on the island of Java will certainly provide an overview of human development that varies spatially (Saputro et al., 2021). Java Island is one of the areas with high population density in Indonesia and has various levels of economic and social development (Trimanto et al., 2023). Thus, the major cities in Java can be considered relevant representations of the variations in welfare conditions that exist in a relatively small regional (Tribhuwaneswari et al., 2022). This allows research to focus more on in-depth spatial analysis related to changes in economic, social, and other factors affecting welfare in these areas (Virtriana et al., 2023).In addition, the more complete and easy-to-find data for big cities in Java Island also makes it a practical choice for spatial research. Therefore, a statistical modelling method is needed by taking into account spatial factors (the influence of the geographical conditions of an area) (Permai et al., 2016). The statistical method that has been developed for data analysis by taking into account spatial factors is Geographically Weighted Regression (Tian et al., 2023). GWR is the development of a regression model in which each parameter is calculated at each location point, so that each geographic location point has a different regression parameter value (Saputra & Radam, 2022)

Based on the prior, the factors influencing the human development index (a measure of prosperity) in Central Java Province are investigated using Ordinary Least Squares regression (Nadya et al., 2016). Geographical Weight Regression will also be used to identify the determinants of welfare in various districts and cities in Central Java (Walsemann et al., 2021).

METHODS

This study uses cross-sectional data, with 34 main cities in Java as the observation unit. The use of major cities in Java as the unit of analysis in this study is based on several sound reasons. Firstly, Java is one of the most populous islands in Indonesia, with some major cities having significant populations.

Therefore, selecting the major cities in Java as the unit of analysis is relevant as they reflect important socio-economic conditions in the Indonesian context. Secondly, major cities on Java Island have diverse economic, social and infrastructural development levels. This provides an opportunity to compare and analyse the differences in spatial welfare levels among these cities, which can provide greater insights. The secondary data is compiled from the sources shown in the table below.

Table 1. Operational Definition

Variable		Variable Indicator	Source	Unit
Dependent (Y)	Well-being	Human Development Index (Y)	opendata.jabar BPS Banten BPS DKI Central Java BPS East Java BPS BPS DIY BPS West Java	Index
Independent (X)	Life expectancy	Age Life Expectancy At Birth (X1)		Years
	Knowledge/Education	Average Length of School (X2)		Years
	Standard of Liability	Expenditures Per Capita (X3)		Thousand Rupiah
	Percentage of Poor Population	Poor Population (X4)		Per cent
	Unemployment	Open Unemployment Rate (X5)		Per cent

Least Square Model Regression

Linear regression analysis is a statistical method used to analyse

factors that influence the variables under study (Nurhalizah & Sitompul, 2022). The result of multiple linear regression is a regression model that describes the relationship between more than one explanatory variable (X) and the response variable (y). (Nadya et al., 2016). The linear regression model in matrix form is:

$$y = \beta_0 + \beta_1 X_1 + + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon$$

Where:

Y: dependent variable of human development index (HDI).

β_0: This is the intercept or constant

β_1, β_2, β_3, β_4: These are regression coefficients that measure the extent to which changes in the independent variables

X_1: Age Life Expectancy at Birth

X_2: Average Years of Schooling

X_3: Per Capita Expenditure

X_4: Poor Population

X_5: Open Unemployment Rate

Regression Assumption Testing

Testing regression assumptions is a critical stage in regression model analysis. First, it is necessary to check whether the regression model is linear in parameters. This is done through visual analysis and statistical tests such as scatter plots and regression tests. Second, it must ensure that the mean value of the errors is zero. This can be tested by calculating the mean of the residuals which should be close to zero. Next, it should check that the variance of the errors is constant or homoscedastic, through a plot of residuals versus predicted values or specialized statistical tests. Autocorrelation in the errors also needs to be avoided, which can be checked with the Durbin-Watson test or autocorrelation plot analysis. Finally, it is necessary to ensure that there is no multicollinearity in the predictor variables, which can be checked by analyzing the correlation between the predictor variables or by calculating the VIF value. In addition, it is necessary to check that the model errors have a near-normal distribution through a normal probability plot or normality test. All these assumptions must be met to ensure the reliability of the regression model and accurate interpretation of the results (Zhu et al., 2020)

Model Parameter Testing

In regression analysis, we conduct two stages of testing that play an important role in assessing the effect of the independent variable on the dependent variable. The first stage is the partial (individual) test. At this stage, we test each independent variable individually. The hypotheses tested are:

H_0 : βi = 0(no significant effect between variables

H_1 : $\beta i \neq 0$, i = 1,2, … , p (there is a significant effect between variables)

The second stage is the simultaneous test. Here, we test all the independent variables simultaneously to assess whether the entire set of independent variables jointly affects the dependent variable in the regression model. The hypotheses tested are:

H_0 : If the significant value of F < 0.05 then H_0 is accepted and H_1 is rejected.

H_1: If the significant value of F > 0.05 then H_1 is accepted and H_0 is rejected.

Geographically Weighted Regression Models

Each parameter in the GWR model is determined locally at each observation site, extending the global regression model (Maulani et al., 2016). This model, a type of local linear regression, produces site-specific parameter estimators (Rafi et al., 2019). According to (Ananda et al., 2023) It is possible to formulate the GWR model as follows

$$\mathrm{yi} = \beta_0(u_o, v_0) + \sum_{k=1}^{p} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i$$

Where:

y_i = the observed value of the response variable i

X_{ik} = the value of the observation of the predictor variable k in the i-th observation

$\beta_0(u_o, v_0)$ = intercept value of the GWR regression model

$\beta_k(u_i, v_i)$ = k-th regression coefficient coordinate point (latitude, longitude) location i

ε_i = Error to i

Geographically Weighted Regression model good fit test

Goodness of Fit (GOF) testing in the Geographically Weighted Regression (GWR) model has an important role in measuring the significance of geographic factors that are at the core of this model, as revealed in research by (Agustina et al., 2015) This test is based on the following hypothesis:

H_0 : βk $(ui$, vi) = βk, k = 1, 2, ... , p (there is no influence of geographical factors on the model, for each i, i = 1, ... , n).

H_1 : There is at least one βk $(ui$, vi) associated with location $(ui$, vi) (there is a geographical factor influence in the model).

To test the significance of the GWR model, test statistics are usually constructed based on the residual sum of squares obtained from the OLS model and the GWR model, as has been found in research by (Lutfiani & Mariani, 2017). This test provides insight into the extent to which geographical factors influence the GWR model and whether this model provides a better explanation than the OLS model (Kashki et al., 2021)

Test the goodness of the model by doing the F test

Testing the goodness of the model using the F test in Geographically Weighted Regression (GWR) is an important step in comparing the performance of the GWR model with the (Ordinary Least Squares) model globally (Kashki et al., 2021). This test helps us to determine which model is better at explaining the variation in the data

$$Fh = \frac{RSS_{OLS} - RSS_{GWR}/V}{RSS_{GWR}/\delta 1} = \frac{GWR_{IMP}/V}{RSS_{GWR}/\delta 1}$$

Where:
Fh: F test statistic used to test the significance of the difference between the OLS and the GWR model.
RSS_{OLS}: This is the residual sum of squares value for the OLS model.
RSS_{GWR}: This is the residual sum of squares value for the GWR model.
V: This is the degree of freedom for the GWR model.
δ1: This is the degree of freedom of the OLS model.
GWR_{IMP}: This test statistic measures the extent to which the GWR model is better at explaining the data than the OLS model. It is used to compare the RSS values between the two models.

In this analysis, we use two parameters, namely v = tr(R_0 – R_1) and δ1 = tr (R_1), to test the difference between the Geographically Weighted Regression (GWR) model and the Ordinary Least Squares (OLS) model. The hypotheses tested are as follows:
H_0: GWR and OLS are the Same
H_1: GWR and OLS are not the Same

If the F test result is not significant, then it can be concluded that there is no significant difference between the GWR model and the OLS model. However, if H_0 is rejected, it indicates a significant difference between these two models. In the case of H_0 rejection, the researcher will proceed to the next steps of the analysis according to the established methodology (Janah & Utami, 2021). This allows us to determine which model is more appropriate or better at explaining the observed data***.***

Partial Test Geographically Weighted Regression

Partial testing of model parameters is an important step in analysing the effect of individual parameters on the model. The purpose of this test is to determine whether a particular parameter, in this case, *$\beta_k = (U_i) = K = 1,2,...p$ and $i = 1,2,....n$),* has a significant influence on the model. The hypothesis tested in this context is as follows:
Hypothesis:
$H_0 : \beta_k (u_i) = 0$
$H_1: \beta_k (u_i) \neq 0$

The statistical tests used in this test are as follows:

$$T = \frac{\widehat{\beta k}(u_i) = 0}{\hat{\sigma}\sqrt{C_{kk}}} \qquad \text{And} \qquad \hat{\sigma} = \frac{SEE(H_1)}{V_1}$$

where σ̂ is the estimated standard error, and C_{kk} is the kth diagonal element of the Ci matrix C_i^T. The test decision is determined by comparing the value of the test statistic T with the critical value |T| > $t_{\alpha/\sum}$ = ($V_{1^{\wedge}2}$)/V_2), where $t_{\alpha/\sum}$ is the critical value corresponding to the significance level α and degrees of freedom V_1 and V_2. If the absolute value of T is greater than the critical value, then H_0 is rejected, which means that the parameter significantly affects the model. Conversely, if the value of T does not exceed the critical value, H_0 is accepted, indicating that the parameter does not significantly affect the model.

RESULTS AND DISCUSSIONS

To determine the welfare of the residents of big cities in Java Island, it is necessary to analyse internal and external factors that can help improve welfare in an area. Therefore, the first step the author takes is to analyse using the global method and geographically weighted regression.

Ordinary Least Square Regression Model

1) Simultaneous test

Simultaneous test is a statistical test used to test simultaneously the effect of several independent variables on the dependent variable in a statistical model. In the context of regression analysis, the simultaneous test is useful for evaluating whether a set of independent variables together have a significant effect on the dependent variable. Simultaneous test results can help determine whether the overall model has a good level of fit with the observed data (Z. Wang et al., 2018).

As for the regression output below, the results of the simultaneous test (F-Stat Test) show that the ordinary last square model formed is good enough (p-value of 0.0000 <0.05) and an R-square of 83.96%. This indicates that the Age Life Expectancy at Birth (X_1), Average Years of Schooling (X_2), Per Capita Expenditure (X_3), Poor Population (X_4), and Open Unemployment Rate (X_5) variables simultaneously affect 83.96% of the welfare variables in big cities on the island of Java. And the rest is influenced by variables outside the model.

2) Partial Test

The test results below show that after being tested partially using a 5% significance level, Age Life Expectancy at Birth (X_1), Average Years of Schooling (X_2), and Per Capita Expenditure (X_3) have a significant effect on the level of community welfare in big cities on the island of Java.

Table 2 Parameter estimation of Ordinary Last Square regression

Table 2. Estimation of Ordinary Least Square regression parameters

Variable	Coefficient	t-stat	p-value	Significance
Intercept	8.340464	0.94	0.345	Not significant
Age Life Expectancy (X_1)	0.833881	6.59	0.000	Significant
Average Years of Schooling (X_2)	0.126059	-5.21	0.000	Significant
Per Capita Expenditure (X_3)	0.007468	6.07	0.000	Significant
Poor Population (X_4)	-0.201337	-1.31	0.201	Not significant
Open Unemployment Rate (X_5)	-0.139697	0.78	0.442	Not significant
F-statistic	0.00000			
R-Square	0.8396			

The optimal worldwide regression model is determined by the results of the parameter significance test mentioned above.

$$\hat{y} = 8.340464 + 0.833881X_1 + 0.126059X_2 + 0.007468X_3 - 0.201337X_4 - 0.139697X_5$$

The level of welfare, as measured by the Human Development Index (HDI), can be explained using this regression model. The intercept (constant) in the model, 8.3404, is the estimate of HDI when all independent variables (X_1, X_2, X_3, X_4, and X_5) are zero. The effect of the variable Age of Life Expectancy at Birth (X_1) on welfare has a positive coefficient of 0.8338, indicating that when the Age of Life Expectancy at Birth increases by one unit (for example, an increase in average life expectancy at birth), welfare tends to increase by 0.833881 units, all other variables held constant. Average Years of Schooling (X_2) on welfare has a positive coefficient of 0.126059, indicating that when Average Years of Schooling increases by one unit (for example, an increase in average years of schooling), welfare tends to increase by 0.1260 units, all other variables held constant.

Per Capita Expenditure (X_3) on welfare has a positive coefficient of 0.007468, indicating that when Per Capita Expenditure increases by one unit (for example, an increase in per capita expenditure), the level of welfare tends to increase by 0.0074 units, all other variables held constant. Poor Population (X_4) on welfare has a negative coefficient of 0.201337, indicating that when the number of poor people increases by one unit (for example, an increase in the number of poor people), the level of welfare tends to decrease by 0.2013 units, all other variables held constant. The Unemployment Rate (X_5) on welfare has a negative coefficient of 0.139697, indicating that when the

Unemployment Rate increases by one unit (for example, an increase in the unemployment rate), the welfare level tends to decrease by 0.1396 units, all other variables being constant.

3) Multicollinearity Assumptions

To find out the presence of multicollinearity in the data, it can be done by calculating the VIF nails in the following table.

Table 3. Multicollinearity test

Variable	VIF	1/VIF
Age Life Expectancy (X_1)	4.42	0.226456
Average Years of Schooling (X_2)	5.72	0.174753
Per Capita Expenditure (X_3)	1.89	0.530168
Poor Population (X_4)	1,54	0.650473
Open Unemployment Rate (X_5)	1.49	0.672213
Mean VIF	3.01	

The test results above show that if the VIF value of the independent variable is less than 10, it means that the non-multicollinearity assumption is met.

4) Normality test

Regarding the test results in the table below, it can be seen (X_5) variables have prob>Z results of more than 0.05, which means these variables are normally distributed.

Table 4. Normality test using the Shapiro-Wilk W test

Variable	Obs	W	V	Z	Prob>Z
Age Life Expectancy (X_1)	34	0.93785	2.170	1.615	0.05320
Average Years of Schooling (X_2)	34	0.62809	12.986	5.342	0.00000
Per Capita Expenditure (X_3)	34	0.94584	1.891	1.328	0.09213
Poor Population (X_4)	34	0.94277	1.998	1.443	0.07457
Open Unemployment Rate (X_5)	34	0.95408	1.608	0.984	0.16264

5) Heteroscedasticity Test

From the test table below, it can be seen that the Prob> Chi 2 value is 0.0616, which means that the decision to reject Ho is fulfilled so that it can be concluded that there is no heterogeneity in the data with α = 5%.

Table 5. Heteroscedasticity test

Chi2(1)	3.49
Prob > Chi 2	0.0616

A. Geographically Weighted Regression Models

1) Geographically Weighted Regression test

GWR analysis cannot be started until the optimal bandwidth is calculated using the minimal CV approach. Analysis using the adaptive Gaussian kernel function yields a minimum CV of 11118385.667, indicating that points within a radius of 0.115357 are ideally important in building the location model parameters. The optimal bandwidth value is calculated to be 0.115357. Having an R^2 value of 84.03%

means that the independent variables used in the GWR model are strong enough to explain the dependent variable.

Table 6. Parameter Coefficient Estimation

Predictor	Min	Q1	Med	Q3	Max
Intercept	-2321,7822	-1171,844	578,0561	5991,02	24417,85
Age Life Expectancy (X_1)	0,097094	0,169048	0,291028	0,29053	0,846261
Average Years Schooling (X_2)	0,119652	0,035355	0,026772	0,215993	0,628982
Per Capita Expenditure (X_3)	-0,086597	-0,046023	0,020098	0,348474	0,58665
Poor Population (X_4)	-2,125346	-0,807250	0,879213	4,394349	8,729943
Open Unemployment Rate (X_5)	-2,645893	2,970690	4,486299	8,415119	13,638493

The table above is a descriptive statistic of the estimated coefficients of the GWR model which includes the minimum value, first quartile, median, third quartile, and maximum value. The GWR model allows the same predictor variable to have a relationship with the response variable that is positive in one location and negative in another. The table above shows that the Life Expectancy variable (X_1) and the average length of schooling (X_2) have a positive influence on the level of community welfare in big cities on the island of Java. While other variables have a positive and negative influence on the location of observation.

2) Fit test models.

After the optimal bandwidth value is obtained, the ideal weighting matrix to generate the GWR model must be determined. In the table below, you can see the weighing results.

Table 7. Fit test models

Residuals	SS	DF	MS	F
Global Residuals	151080650,982	28,000		
GWR Improvement	66617575,386	5,513	12082641,344	
GWR Residuals	284463075,595	22,487	8203278,841	2,772904

The GWR ANOVA table information is used to see if the GWR model is better than the OLS (global regression) model. The GWR model is better than the OLS model if the sum square GWR residuals value is smaller than the sum square global residuals. This can be proven again with the F test, which compares the calculated F value with the F table whether it is significant or not. In the results above, the calculated F value is 2.772904 with a degree of freedom (5.513; 22.487) and with a significance level of 0.05, the F table value is 2.66127. So, it can be concluded that the GWR model is significantly better than the OLS model.

3) Partial test of Geographically Weighted Regression Model Global Predictor Variables

The table below can be used as part of a geographic factor impact partial test for each predictor variable, revealing which variables have different effects depending on the location of observation

Table 8. partial test of the global predictor variable GWR model

Variable	F	DOF for	F-test	DIFF of Criterion
Intercept	1,523214	0,479	24,685	-6370,629400
Age Life Expectancy (X_1)	1,441280	0,540	24,685	-250839,256052
Average Years Schooling (X_2)	1,113253	0,517	24,685	-31511,647417
Per Capita Expenditure (X_3)	3,568909	0,447	24,685	112215,896773
Poor Population (X_4)	3,081017	0,400	24,685	-158866,868469
Open Unemployment Rate (X_5)	1,119225	0,433	24,685	2505,833297

GWR partial test can be seen from the DIFF of criteria value. A negative DIFF of criterion value indicates that the independent variable has significant spatial variability or spatial heterogeneity locally. So it can be concluded if the variables of Life Expectancy (X_1), Average Years of Schooling (X_2), Poor Population(X_4) have a local effect. Meanwhile, Expenditure per Capita (X_3) and the unemployment rate (X_5) have no local effect in all observation locations.

The model acquisition of the level of welfare in big cities on Java Island with the OLS method can be written as follows

$$\hat{y} = 8.340464 + 0.833881X_1 + 0.126059X_2 + 0.007468X_3 - 0.201337X_4 - 0.139697 X_5$$

Following the model above, it can be seen that if life expectancy (X_1) increases, the level of social welfare will also increase by 0.833881 or vice versa. this means that life expectancy has a positive relationship to well-being. Variable Average Length of School (X_2) also has a negative effect on the level of welfare. If the average length of schooling increases the number of years spent in school, then welfare will also decrease by 0.126059 assuming other variables are held constant. The results of this study indicate that with an increase in the average length of school, welfare will increase. Likewise, the Per Capita Expenditure variable (X_3) has a positive effect on welfare. This shows that if there is an increase in per capita expenditure, it can be said that the level of social welfare will also increase by 0.007468 assuming other variables are held constant. Meanwhile, the poor Population variable (X_4) has a negative effect on the level of social welfare in big cities on the island of Java. Given that if there is an increase in the poverty rate, it will connote a decrease in the level of community welfare by 0.201337. In addition, the unemployment variable (X_5) also has a negative and not significant relationship to welfare. In theory, the relationship between unemployment and welfare is positive; if there is an increase in the number of unemployed, the level of welfare will decrease. The Geographically Weighed Regression (GWR) model is as follows:

$$\hat{y} = 0,079174 + 0,213574X_1 +0,115500X_2 -0,352727X_3 - 0,528005X_4 + 1,333181X_5$$

Based on the model above, the variable that has an effect on the level of well-being is life expectancy (X_1). This means that if the level of life expectancy increases, it means that the level of welfare will also increase, and vice versa. The average length of school variable (X_2) also has a significant influence on the level of welfare, where when the average length of school increases, the level of welfare will also increase. And the least variable that has a significant effect is the poverty (X_4) variable, where the poverty variable has a negative influence on the level of welfare.

Java Island has 34 cities with 6 provinces administratively. The spatial results for each region on the distribution of welfare levels are as follows

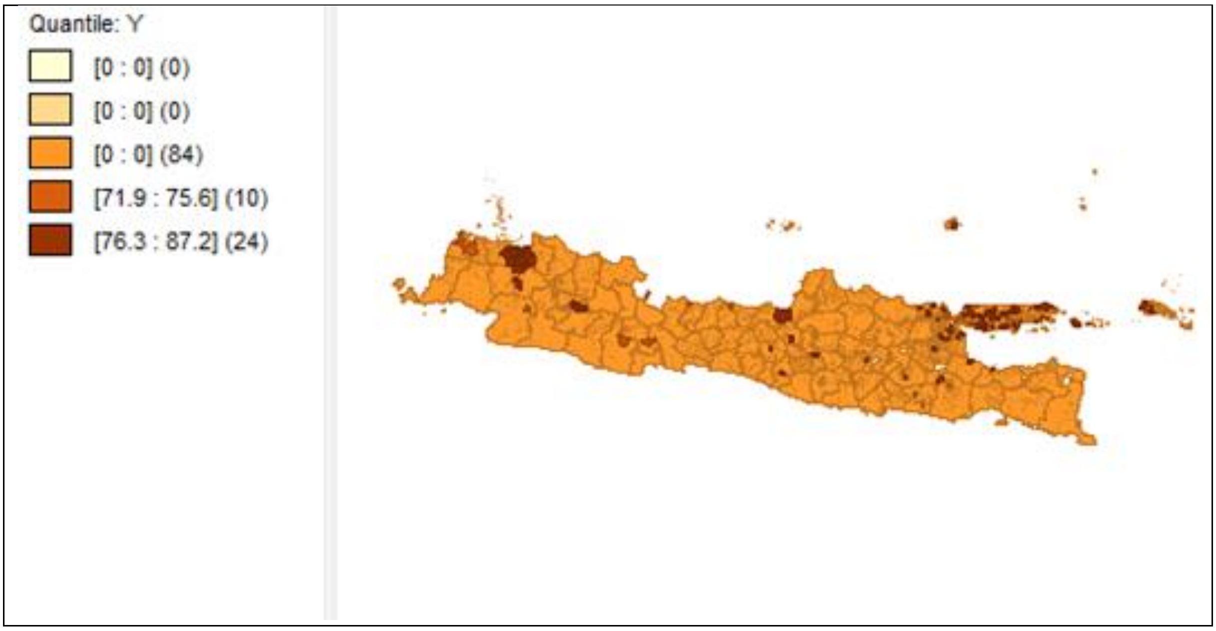

Figure 1. Map of the distribution of the level of welfare of urban residents on the island of Java in 2021

The level of welfare in the big cities of Java Island based on the distribution shows that the level of welfare in cities tends to be low including Banjar City, Cilegon City, Cirebon City, Pasuruan City, Pekalongan City, Probolinggo City, Serang City, Sukabumi City, Tasikmalaya City, and the City of Tegal. The other 24 cities have a high level of welfare compared to other cities on the island of Java. To see the distribution of life expectancy for each existing location, it is illustrated on the map below:

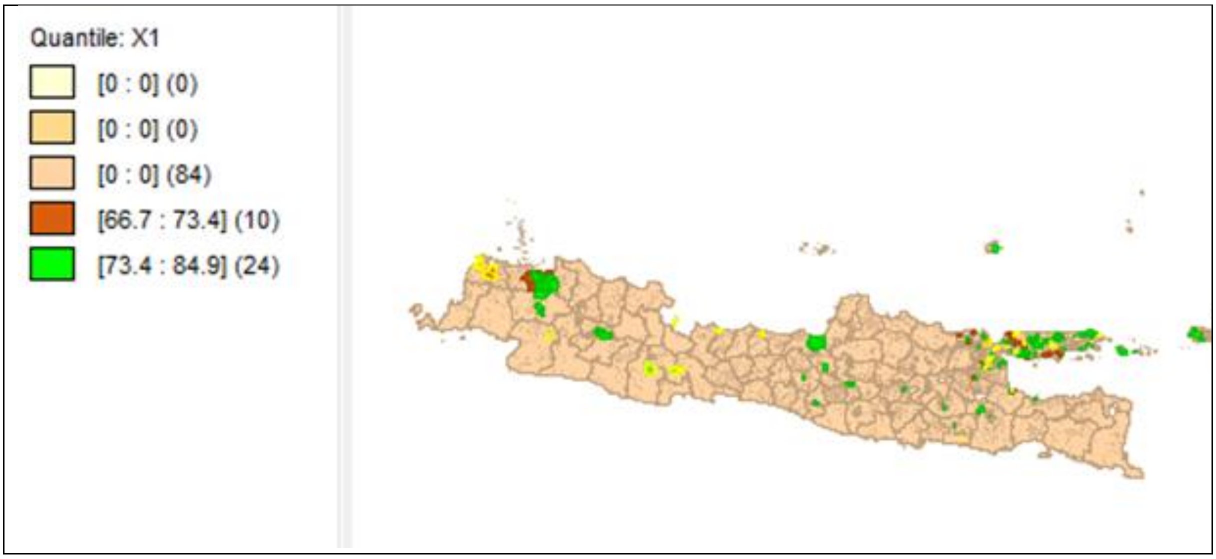

Figure 2. Map of the distribution of life expectancy rates for urban residents on the island of Java in 2021

Based on the distribution, life expectancy in big cities on the island of Java shows that 10 cities tend to be low, including North Jakarta, Batu City, Cilegon City, Madiun City, Malang, Pasuruan, Probolinggo, Serang, Landing, and South Tangerang City. The cities that have an average distribution of school years in each region are described in the map below:

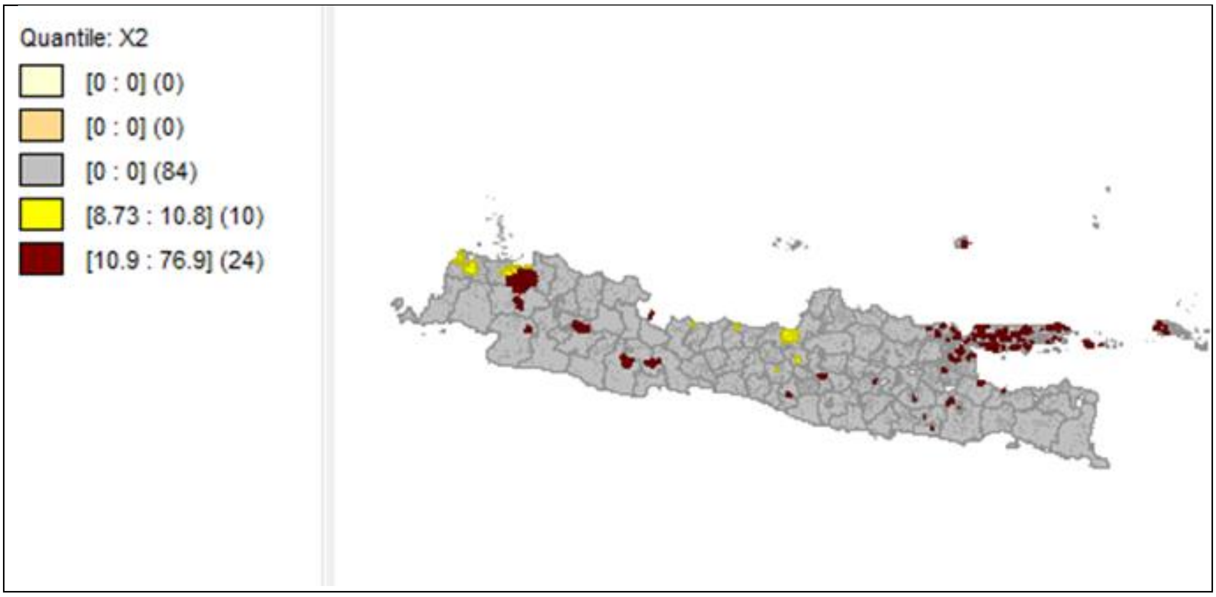

Figure 3. Distribution of the average length of schooling for urban residents on the island of Java in 2021

The average length of schooling in major cities on the island of Java based on distribution shows that 10 cities have a low average length of schooling including the cities of West Jakarta, North Jakarta, Cilegon City, Magelang, Pekalongan, Salatiga, Semarang, Serang, Tangerang, and the city of Tegal.

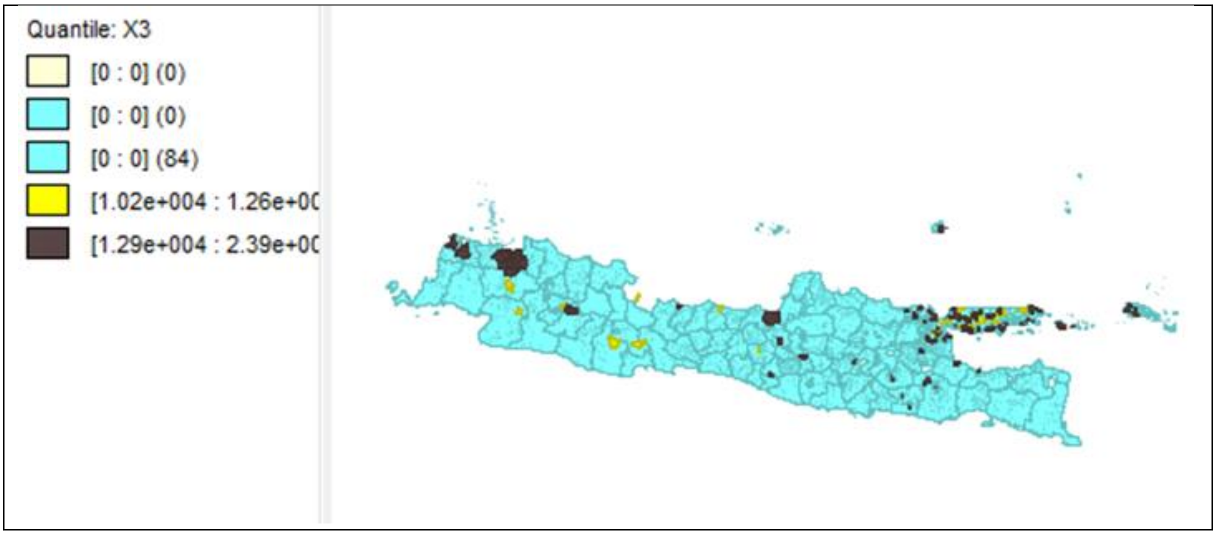

Figure 4. Distribution of expenditure levels per capita of urban residents on the island of Java in 2021

Following the map image above, the cities that have low spending levels are the city of Banjar, Bogor city, Cimahi city, Cirebon city, Kediri city, Magelang city, Pekalongan city, Probolinggo city, Sukabumi city, and Tasikmalaya city. To find out the distribution of the poverty rate in the big cities of Java Island, it is illustrated on the map below:

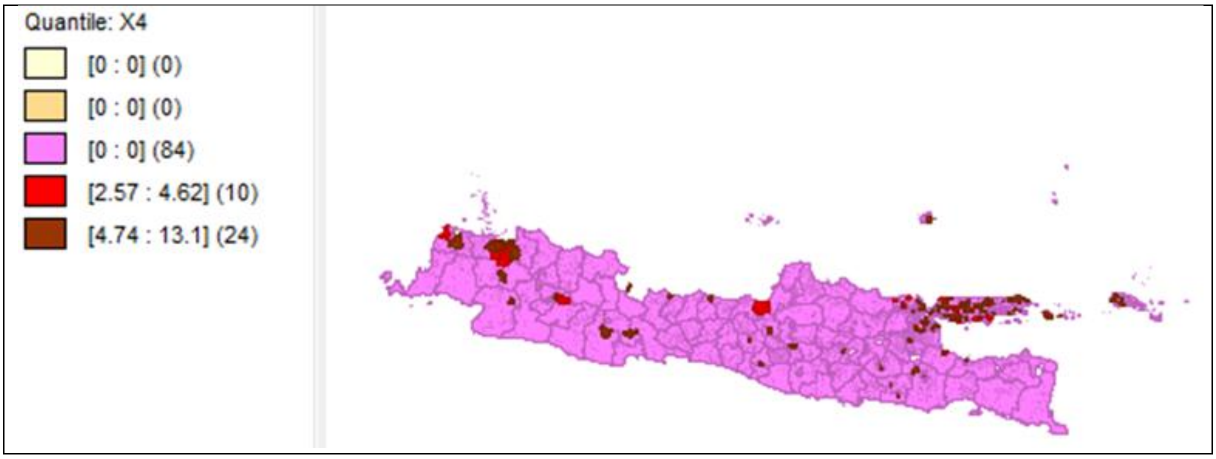

Figure 5. the distribution of poverty rates for urban residents on the island of Java in 2021

The number of urban poor people on the island of Java, based on its distribution, shows that the number of poor people in cities tends to be low, including the cities of West Jakarta, South Jakarta, East Jakarta, Bandung City, Batu City, Cilegon City, Depok City, Malang City, Semarang City, Landing City. south. While in the very high percentage category there are 24 other cities on the island of Java with a distribution of poor population as shown in Figure 5. Cities that have a high unemployment rate compared to other cities are illustrated in the map below:

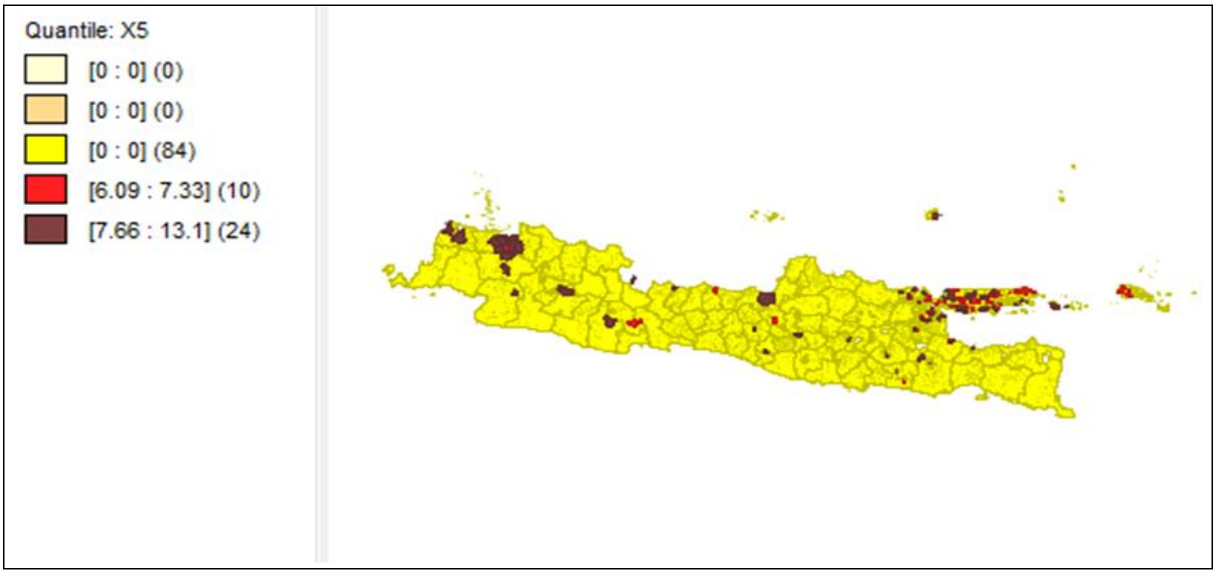

Figure 6. The distribution of unemployment rates for urban residents on the island of Java in 2021

Commencing from the unemployment rate distribution map, the cities in the high category are West Jakarta, Central Jakarta, East Jakarta, North Jakarta, Bandung City, Bekasi City, Bogor City, Cilegon City, Cimahi City, Cirebon City, Depok City, Magelang City, Malang City, the city of Semarang, the city of Serang, the city of Sukabumi, the city of Surabaya, the city of Surakarta, the city of Tangerang, the city of Tasikmalaya, the city of Tegal, and the city of Yogyakarta

CONCLUSIONS

Based on the results of the analysis described in the discussion section, it can be concluded that GWR capitalization is better in describing the level of community welfare in big cities in Java. This is evidenced by the results of R^2 testing Geographically Weighted Regression is greater than the results of R^2 using Ordinary Least Square. The results of this study can be used as local policy making based on factors that affect the region.

The variables in the Ordinary least square test that have a significant influence on the level of welfare are the variables of Life Expectancy (X1), Average years of schooling (X2), and per capita expenditure (X3) for the big cities of Java Island in 2021. Meanwhile, the test results using Geographically Weighted Regression show that the dominant factors that significantly affect the level of welfare in each city on the island of Java are the variables of Life Expectancy (X1), Average Years of Schooling (X2), Poor Population (X4) which have a local effect.

Suggestions that can be given for future research are factors that have a significant influence in this study both using the Ordinary least square test and using the Geographically Weighted Regression test can be taken into consideration for the government in making decisions to improve community welfare. In addition, spatial regression research with a location approach, namely Geographically Weighted Regression, can add other factors to deepen and expand this research. This is because the results of testing this research are still many other variables that can be added so that it can provide a great opportunity for other researchers to be further developed.

REFERENCES

Agustina, M. F., Wasono, R., & Darsyah, Moh. Y. (2015). *Pemodelan Geographically Weighted Regression (GWR) Pada Tingkat Kemiskinan di Provinsi Jawa Tengah* (Vol. 3, Issue 2).

Ananda, N. M. S., Suyitno, S., & Siringoringo, M. (2023). Geographically Weighted Panel Regression Modelling of Human Development Index Data in East Kalimantan Province in 2017-2020. *Jurnal Matematika, Statistika Dan Komputasi*, *19*(2), 323–341. https://doi.org/10.20956/j.v19i2.23775

Arthayanti, Y., Srinadi, I. G. A. M., & Gandhiadi, G. K. (2017). Geographically Weighted Ridge Regression dalam Kasus Multikolinearitas Pada Indeks Pembangunan Manusia di Kabupaten/Kota Provinsi Jawa Timur. *Jurnal Matematika*, *7*(2), 124. https://doi.org/10.24843/jmat.2017.v07.i02.p89

Borjas, G. J. (2016). Does welfare reduce poverty? *Research in Economics*, *70*(1), 143–157. https://doi.org/10.1016/j.rie.2015.11.002

Case, K. E., & Fair, R. C. (2003). *Prinsip-Prinsip Ekonomi* (Erlangga, Ed.; Edisi Ketujuh).

Chakraverty, S., & Gupta, D. (2022). As a pandemic strikes: A study on the impact of mental stress, emotion drifts and activities on community emotional well-being. *Measurement: Journal of the International Measurement Confederation*, *204*(September), 112121. https://doi.org/10.1016/j.measurement.2022.112121

Collins, B. (2017). Results from a Well-Being Survey in the North West of England: Inequalities in EQ-5D–Derived Quality-Adjusted Life Expectancy Are Mainly Driven by Pain and Mental Health. *Value in Health*, *20*(1), 174–177. https://doi.org/10.1016/j.jval.2016.08.004

Cui, X., & Chang, C. Ter. (2020). How life expectancy affects welfare in a Diamond-type overlapping generations model. *Physica A: Statistical Mechanics and Its Applications*, *555*, 124616. https://doi.org/10.1016/j.physa.2020.124616

Djokoto, J. G., & Wongnaa, C. A. (2023). Does the level of development distinguish the impacts of foreign direct investment on the stages of human development? *Sustainable Futures*, *5*(November 2022), 100111. https://doi.org/10.1016/j.sftr.2023.100111

Fahrudin, A. (2012). *Pengantar Kesejahteraan Sosial*. PT Refika Aditama.

Freire, R. C., Pieruccini-Faria, F., & Montero-Odasso, M. (2018). Are Human Development Index dimensions associated with gait performance in older adults? A systematic review. *Experimental Gerontology*, *102*(December 2017), 59–68. https://doi.org/10.1016/j.exger.2017.12.001

Giacalone, M., Mattera, R., & Nissi, E. (2022). Well-being analysis of Italian provinces with spatial principal components. *Socio-Economic Planning Sciences*, *84*. https://doi.org/10.1016/j.seps.2022.101377

Hartanto, W., Islami, N. N., Mardiyana, L. O., Ikhsan, F. A., & Rizal, A. (2019). Analysis of human development index in East Java Province Indonesia. *IOP Conference Series: Earth and Environmental Science*, *243*(1). https://doi.org/10.1088/1755-1315/243/1/012061

Janah, L. M., & Utami, T. (2021). *PERBANDINGAN METODE GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) DAN ORDINARY LEAST SQUARE (OLS) DALAM PEMODELAN KETIMPANGAN DI PROVINSI JAWA TENGAH*.

Kadri, I. A., Susilawati, M., & Sari, K. (2020). FAKTOR–FAKTOR YANG BERPENGARUH SIGNIFIKAN TERHADAP INDEKS PEMBANGUNAN MANUSIA DI PROVINSI PAPUA. *E-Jurnal Matematika*, *9*(1), 31. https://doi.org/10.24843/mtk.2020.v09.i01.p275

Kartika, S., & Kholijah, G. (2020). Penggunaan Metode Geograhically Weighted Regression (GWR) Untuk Mengestimasi Faktor Dominan yang Mempengaruhi Penduduk Miskin di Provinsi Jambi. *JOMTA Journal of Mathematics: Theory and Applications*, *2*(2).

Karyono, Y., Tusianti, E., Gunawan, I. G. N. A. R., Nugroho, A., & Clarissa, A. (2021). *Indeks Pembangunan Manusia* .

Kashki, A., Karami, M., Zandi, R., & Roki, Z. (2021). Evaluation of the effect of geographical parameters on the formation of the land surface temperature by applying OLS and GWR, A case study Shiraz City, Iran. *Urban Climate*, *37*(September 2020), 100832. https://doi.org/10.1016/j.uclim.2021.100832

Lutfiani, N., & Scolastika Mariani, dan. (2017). Pemodelan Geographically Weighted Regression (GWR) dengan Fungsi Pembobot Kernel Gaussian dan Bi-square. In *UNNES Journal of Mathematics* (Vol. 5, Issue 1). http://journal.unnes.ac.id/sju/index.php/ujmUJM8

Martínez-Guido, S. I., González-Campos, J. B., & Ponce-Ortega, J. M. (2019). Strategic planning to improve the Human Development Index in disenfranchised communities through satisfying food, water and energy needs. *Food and Bioproducts Processing*, *117*, 14–29. https://doi.org/10.1016/j.fbp.2019.06.007

Maulana, A., Meilawati, R., & Widiastuti, V. (2019). *Pemodelan Indeks Pembangunan Manusia (IPM) Metode Baru Menurut Provinsi Tahun 2015 Menggunakan Geographically Weighted Regression (GWR)*.

Maulani, A., Herrhyanto, N., & Suherman, M. (2016). *APLIKASI MODEL GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) UNTUK MENENTUKAN FAKTOR-FAKTOR YANG MEMPENGARUHI KASUS GIZI BURUK ANAK BALITA DI JAWA BARAT*.

Murni, J. M., Terapan, D., Qomariyah, N., Susanti, D. S., & Salam, N. (2018). *ESTIMASI PARAMETER MODEL REGRESI TERBOBOTI GEOGRAFIS (STUDI KASUS TINGKAT KESEJAHTERAAN PENDUDUK DI KABUPATEN BANJAR)*. *12*(1), 1–10.

Mursito, T. P. A. P., Berlianto, M. C., An'amtaAdinindra, Y., Edbert, I. S., & Ohyver, M. (2022). Modeling the Amount of Poverty in Central Java using Geographically Weighted Regression. *2022 International Conference on Science and Technology (ICOSTECH)*, 1–6. https://doi.org/10.1109/ICOSTECH54296.2022.9828815

Nadya, M., Rahayu, W., & Santi, V. M. (2016). *ANALISIS GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) PADA KASUS PNEUMONIA BALITA DI PROVINSI JAWA BARAT*.

Nurhalizah, & Sitompul, P. (2022). Analysis of Ordinary Least Square and Geographically Weighted Regression on the Human Development Index of North Sumatra 2021. *Formosa Journal of Applied Sciences*, *1*(6), 981–1000. https://doi.org/10.55927/fjas.v1i6.1718

Permai, S. D., Tanty, H., & Rahayu, A. (2016). Geographically weighted regression analysis for human development index. *AIP Conference Proceedings*, *1775*. https://doi.org/10.1063/1.4965165

Qiu, Q., Sung, J., Davis, W., & Tchernis, R. (2018). Using spatial factor analysis to measure human development. *Journal of Development Economics*, *132*(October 2017), 130–149. https://doi.org/10.1016/j.jdeveco.2017.12.007

Rafi, A., Diastina, N., Handajani, S. S., & Slamet, I. (2019). ANALISIS MODEL GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) PADA KASUS JUMLAH PESERTA KB AKTIF DI PROVINSI JAWA TENGAH. *PROSIDING SEMINAR NASIONAL GEOTIK 2019. ISSN: 2580-8796364*.

Reskia, A. (2022). *ANALISIS SPASIAL TINGKAT KESEJAHTERAAN DI INDONESIA MENGGUNAKAN GEOGRAPHICALLY WEIGHTED LOGISTIC REGRESSION*.

Riccardi, E., Fontana, L., Pacella, D., Fusco, F., Marinaro, I., Costanzo, G., Vassallo, F., Triassi, M., & Iavicoli, I. (2023). Impact of Covid-19 pandemic on psychological well-being of firefighters. *Safety and Health at Work*, *xxxx*. https://doi.org/10.1016/j.shaw.2023.06.002

Sadarrudin, M. A. P. A., Rochaida, E., Hasid, Z., & Suharto, R. B. (2022). Causality between Regional Economic Independence and Decentralization on Poverty Alleviation and Community Welfare Mediated by Economic Development. *International Journal of Sustainable Development and Planning*, *17*(2), 623–632. https://doi.org/10.18280/ijsdp.170227

Saputra, H. Y., & Radam, I. F. (2022). Accessibility model of BRT stop locations using Geographically Weighted regression (GWR): A case study in Banjarmasin, Indonesia. *International Journal of Transportation Science and Technology*, *12*(3), 779–792. https://doi.org/10.1016/j.ijtst.2022.07.002

Saputro, D. R. S., Hastutik, R. D., & Widyaningsih, P. (2021). The modeling of human development index (HDI) in Papua - Indonesia using geographically weighted ridge regression (GWRR). *AIP Conference Proceedings*, *2326*. https://doi.org/10.1063/5.0040329

Sarabhai, Vikram. A. (1975). *POVERTY AND ECONOMIC DEVELOPMENT*.

Shintia Dewi, F., & Yasin, H. (2015). *PEMODELAN STATUS KESEJAHTERAAN DAERAH KABUPATEN ATAU KOTA DI JAWA TENGAH MENGGUNAKAN GEOGRAPHICALLY WEIGHTED LOGISTIC REGRESSION SEMIPARAMETRIC*. *4*(1), 43–52. http://ejournal-s1.undip.ac.id/index.php/gaussian

Tian, M., Wang, X., Wang, Q., Qiao, Y., Wu, H., & Hu, Q. (2023). Geographically weighted regression (GWR) and Prediction-area (P-A) plot to generate enhanced geochemical signatures for mineral exploration targeting. *Applied Geochemistry*, *150*(November 2022), 105590. https://doi.org/10.1016/j.apgeochem.2023.105590

Tribhuwaneswari, A. B., Hapsery, A., & Rahayu, W. K. (2022). Spatial autoregressive quantile regression as a tool for modelling human development index factors in 2020 East Java. *AIP Conference Proceedings*, *2668*(October). https://doi.org/10.1063/5.0112828

Trimanto, Metusala, D., Erlinawati, I., Angio, M. H., Yusuf, H. M., & Budiarto, K. (2023). Study of population and conservation of Dendrobium capra J.J. Smith, an endangered and endemic orchid from Java Island, Indonesia. *Journal for Nature Conservation*, *75*(May), 126476. https://doi.org/10.1016/j.jnc.2023.126476

Virtriana, R., Deanova, M. A., Safitri, S., Anggraini, T. S., Ihsan, K. T. N., Deliar, A., & Riqqi, A. (2023). Identification of land cover change and spatial distribution based on topographic variations in Java Island. *Acta Ecologica Sinica*, *April*. https://doi.org/10.1016/j.chnaes.2023.08.002

Walsemann, K. M., Fisk, C. E., & Dues, A. N. (2021). A spatial analysis of county-level education context and population health and wellbeing. *Wellbeing, Space and Society*, *2*. https://doi.org/10.1016/j.wss.2020.100002

Wang, J., Wang, C., Li, S., & Luo, Z. (2021). Measurement of relative welfare poverty and its impact on happiness in China: Evidence from CGSS. *China Economic Review*, *69*(November 2020), 101687. https://doi.org/10.1016/j.chieco.2021.101687

Wang, Z., Danish, Zhang, B., & Wang, B. (2018). Renewable energy consumption, economic growth and human development index in Pakistan: Evidence form simultaneous equation model. *Journal of Cleaner Production*, *184*, 1081–1090. https://doi.org/10.1016/j.jclepro.2018.02.260

Yamada, E., & Shimizutani, S. (2022). The COVID 19 pandemic, daily mobility and household welfare: Evidence from Tajikistan. *Transportation Research Interdisciplinary Perspectives*, *15*(February), 100641. https://doi.org/10.1016/j.trip.2022.100641

Zhu, C., Zhang, X., Zhou, M., He, S., Gan, M., Yang, L., & Wang, K. (2020). Impacts of urbanization and landscape pattern on habitat quality using OLS and GWR models in Hangzhou, China. *Ecological Indicators*, *117*(July), 106654. https://doi.org/10.1016/j.ecolind.2020.106654