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Factors affecting poverty using a geographically weighted regression approach (case study of Java Island, 2020)

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ABSTRACT

Poverty is still the main problem in development both at the national and regional levels. The poverty reduction program carried out has not paid attention to spatial aspects so that the policies taken are often not on target. This study aims to see the spatial pattern of poverty in Java Island which includes Banten, DKI Jakarta, West Java, Central Java, DI Yogyakarta and East Java. The method used is geographically weighted regression (GWR) with addiptive weighting of the Gaussian Kernel which is processed with QGIS, Geoda and GWR4 software. This approach can identify spatial patterns that cannot be identified in ordinary regression analysis as found in previous studies. The data used in this study is secondary data in 2020 sourced from the Badan Pusat Statistik (BPS) and government website. The results of the study showed positive and group spatial autocorrelation in 34 districts/cities. There are 65 districts/cities in Java Island only affected by HDI, 4 districts/cities affected by TPT and HDI, 47 districts/cities affected by MSEs and HDI, and 3 districts/cities affected by TPT, UMK and HDI. The government can improve the quality of education, the level of public health services, and provide job training to reduce poverty.

Introduction

Poverty is a condition of not being able to meet certain basic needs standards, such as food, health and education. The Indonesian government has made poverty a major problem that must be resolved. Various strategies and programs have been implemented to reduce poverty. These programs include Program Keluarga Harapan (PKH), Beras Miskin (Raskin), Program Inpres Desa Tertinggal (IDT), Kredit Usahatani Rakyat (KUR), and Jaminan Kesehatan Masyarakat (JAMKESMAS) which have not yielded optimal results (Rofiq, 2014). The problem of poverty in Indonesia is still not fully resolved, especially in Java. Java is an island that is the center of national economic growth. However, Java has the highest number of poor people compared to other islands in Indonesia. According to Badan Pusat Statistik for 2020, there are 14.75 million people living in poverty in Java or around 53% of the total poor population in Indonesia. This shows that the poverty rate on the island of Java is still relatively high. The problem of poverty that has not been fully resolved in Java is caused by several problems. First, population density in Java Island occupies the first position in Indonesia in 2020. Second, the amount of GDP in Java Island is the largest in Indonesia. Third, the largest urbanization occurred on the island of Java, so that poverty patterns in Java can be used as a reference for mapping poverty patterns in other regions. Because each region has different characteristics, it is not possible to identify regional poverty factors using the same analytical method (Pribadi & Kartiasih, 2020). Regional characteristics are very important to be used as a factor in the poverty analysis approach (Sholihin et al., 2017).

One possible approach to analyzing an area regarding poverty is a spatial approach. Spatial approach is used to see the distribution and geographical location factors that influence. Differences in geographic location affect the potential of a region. Therefore, a statistical modeling method is needed that considers geographical location. One method of analysis that takes into account geographic location is the Geographically Weighted Regression (GWR) model. The GWR model is a further development of the linear regression model. The linear regression model only produces globally valid parameter estimates, while the GWR model produces localized model parameter estimates for each observation location (Widiyanti et al., 2014). Several studies on poverty have been carried out Sukanto et al (2019) found that 25 sub-districts in Pandeglang and Lebak Regencies have positive spatial autocorrelation. Village funding, electricity, and roads tend to have a poverty reduction effect in 80 percent of the sub-districts in Pandeglang and Lebak districts. In addition, net enrollment rates tend to have a poverty reduction effect in all sub-districts in Pandeglang and Lebak districts. Astuti et al (2018) found that the percentage of poor households using clean water and the percentage of poor people aged 15 years and over with non-working status tended to reduce the poverty rate in 9 regencies/cities in East Tenggara Timur, while the percentage of poor households who received poverty reduction instruments and the percentage of poor households using clean water tends to reduce poverty rates in 8 districts/cities in East Tenggara Timur.

Based on the above problems, a poverty alleviation policy is needed in Java by taking into account the spatial aspect so that it will lead to policies that are right on target. This is because research on poverty by considering geographical differences between districts/cities is rarely carried out, so researchers use the Geographically Weighted Regression (GWR) approach to differentiate it from previous studies which mostly used ordinary regression analysis. Using this approach it is possible to identify spatial patterns that might be missed in ordinary regression analysis. In addition, this research focuses on 2020 because it is hoped that this research will be

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able to assist in providing focused and actual insights into the factors that affect poverty in a certain period of time.

Method

Variables Description

Poverty is a condition of a society that is economically unable to meet the necessities of life in accordance with the standard of living of an area. This situation can be identified by detecting conditions such as an income that is too low to meet basic needs (food, clothing, and shelter). The low income of the community also has an impact on fulfilling needs such as the need for public health and the need for education which is becoming inadequate. This can produce the same cycle for the next generation, making it increasingly difficult for poor families to get out of poverty. UU no. 24 of 2004 explains that poverty is a socio-economic condition of people who are unable to meet the needs of basic rights for the defense and development of life in order to have dignity. According to Prawoto (2009) understanding poverty and strategies for overcoming it, it is known that there are mistakes in tackling poverty. This is because the analysis carried out uses variables that are not significant for poverty alleviation. Analysis aimed at overcoming poverty should use analysis that is significant for overcoming poverty, namely variables related to increasing capacity and productivity, by increasing the basic capabilities of the poor to increase income and overcome poverty. So, this is in line with the poverty analysis by including the HDI and minimum income variables.

The Central Bureau of Statistics (BPS) defines the unemployment rate as the percentage of unemployed people compared to the number of people included in the labor force. The labor force is defined as the population aged 15 years and over who are employed, have jobs but are temporarily unemployed, and are unemployed. The United Nations (UN) explained in an article on its website that unemployment is one of the problems that causes poverty because as we know, for people, work is a way to earn income to make ends meet. In addition Todaro & Smith (2012) explains that unemployment has a very close relationship in influencing poverty levels. The low standard of living is manifested qualitatively and quantitatively in the form of very low income levels, inadequate housing, poor health, minimal or even no educational provision, high infant mortality rates, relatively very long life expectancy. short and the chances of getting a job are low. High unemployment will cause income to decrease so that it cannot meet daily needs which will eventually experience poverty, thus the number of unemployed has a positive relationship to poverty. Research conducted by Yacoup (2012) regarding whether there is an effect of the unemployment rate on poverty in West Kalimantan Province shows that unemployment has a significant effect on the poverty rate with a relationship pattern that is not always one way.

Human Development Index (HDI) is a number that shows how the population can access development to earn income, obtain health, education and other facilities. This figure also measures the government's success in providing the best quality of life for the people. According to Kuncoro, the main focus in development is improving human quality, where human quality can be measured by an index called HDI. The low Human Development Index (HDI) will result in low work productivity of the population. Low productivity results in low revenue gain. So that with low income causes a high number of poor people. Research on the factors that influence poverty was conducted by Pratama (2014) using the multi-regression method showing the result that the HDI is one of the factors that significantly influences poverty, the higher the HDI, the less poverty it can affect. The relationship between HDI and poverty is explained as a negative relationship. In addition, research was also conducted by Fadila & Marwan (2020) found that by using panel data regression the Human Development Index negative and significant effect on poverty in West Sumatra Province. This means that increasing the Human Development Index will reduce poverty in the province of West Sumatra. Conversely, a decrease in the value of the Human Development Index causes an increase in poverty in the province of West Sumatra.

Regional Minimum Wage (Wage) is a government stipulation regarding the lowest income that is applied to an area, in which companies are required to pay at least the same as decent living needs in that area for workers with the lowest level. The minimum wage policy is implemented on consideration of increasing the welfare of the community, especially the welfare of the poor. An increase in the minimum wage is expected to be able to increase income for workers that can be used to meet their daily needs, which in turn will have an impact on reducing the poverty rate in society. Research using panel data regression was conducted by Wuranti (2022) regarding the factors that influenced poverty in East Java in 2008-2013, in this study the results showed that the minimum wage had a negative effect on poverty. The provision of this minimum wage is expected to increase worker productivity, so that they have a decent income, and then improve people's living standards.

Gross Regional Domestic Product (GRDP) per capita is GRDP divided by the number of residents in the area at a certain time. Negative economic growth can lead to increased poverty (Ishengoma & Kappel, 2006). Economic growth is the main driver in reducing or increasing poverty (Fosu, 2017). Sudiharta & Sutrisna (2014) in his research on factors that influence poverty, GRDP per capita with the Granger causality test of the VAR analysis is known to have an effect on poverty in the Province of Bali, in this case it is described as an increase in output along with many people working, so that unemployment and poverty decrease.

This study uses secondary data for the 2020 period obtained from the Central Bureau of Statistics (BPS) and Big Data such as government websites with research object locations on Java

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Island, consisting of the provinces of West Java, East Java, DI Yogyakarta, DKI Jakarta, Banten, and Central Java. The research method used is Geographically Weighted Regression (GWR) with additive Gaussian Kernel Weighing processed with QGIS, Geoda, and GWR4 software to see spatial effects (Nashwari et al., 2017). According to Bappenas (2008) the factors that cause poverty include economic, social, and physical aspects.

Geographically Weighted Regression

GWR is a non-stationary technique that models spatially varying relationships which is an extension of the linear regression model (Caraka & Yasin, 2017). Compared to baseline (global) regression, the coefficient in GWR is a function of spatial location (Lu et al., 2014). Because each region has different characteristics, it is not possible to identify regional poverty factors using the same analytical method. So the GWR model is used to see the variation in spatial (geographical) effects that may exist in the relationship between the dependent and independent variables in all regions in the model. The advantage of the GWR mode compared to the classical regression model is that the GWR is able to provide the mode locally. The general form of the basic GWR model is as follows:

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} x_{ik} + \varepsilon_i \tag{1}$$

Where y_i is the dependent variable at the i-th location; x_{ik} is the k-th independent variable at the i-th location; m is the number of independent variables; β_{i0} is the intercept parameter at the i-th location; β_{ik} is the local regression coefficient for the k-th independent variable at location-i and ε_i is the random error at location i. The GWR allows the coefficients to vary continuously across the study area, and a set of coefficients can be estimated at any location, typically on a grid, so that surface coefficients can be visualized and interrogated for relationship heterogeneity. The GWR makes decision-point calibrations of "influence bumps" around each regression point where closer observation has a greater influence in estimating the local set of coefficients than more distant observations. In essence, GWR measures the adherence around each i-th regression point, where each set of regression coefficients is estimated by weighted least squares. Estimation is formulated in the estimation matrix as follows:

$$\widehat{\beta_i} = (X^T W_i X)^{-1} X^T W_i y \tag{2}$$

where X is a matrix of independent variables with a first column for the intercept; y is the dependent variable vector; $\widehat{\beta_i} = (\beta_{i0}, \ldots \beta_{im})^T$ is a vector of m+1 local regression coefficients; and W_i is a diagonal matrix that shows the geographic weight of each observational data for the i-th regression point. In this case, the weighting scheme Wi is calculated by the kernel function based on the proximity between the regression point i and the N data points around it. Any number of function kernels can be used for the weighting scheme, where for this study a Gaussian kernel is determined, which in continuous form can usually be defined as follows:

$$Gaussian: w_{ij} = exp\left[-\frac{1}{2}(\frac{d_{ij}}{b})^2\right] \tag{3}$$

Where d_{ij} is the distance between observation point j and the ith regression point; ED is generally used with planar coordinates; and b is the kernel bandwidth. Bandwidth is the main controlling parameter and can be determined either by a fixed distance or by a fixed number of nearest neighbors. GWR defaults to global fit regression if very large bandwidths are defined such that all geographic weights tend to come together. Optimal bandwidth can be obtained by minimizing some of the goodness of fit diagnostic models, such as the cross-validation score (CV) which only takes into account the prediction accuracy of the model, or the Akaike Information Criterion (AIC), which describes the model sparingly (i.e., a trade-off between prediction accuracy and complexity). In practice, a corrected version of AIC is used, which unlike the basic AIC is a function of sample size. So, for the GWR model with bandwidth b, the AIC can be found at:

$$AIC_c(b) = 2n\ln(\hat{\sigma}) + n\ln(2\pi) + n\left\{\frac{n = tr(S)}{n - 2 - tr(S)}\right\} \tag{4}$$

Where n is the sample size; $\hat{\sigma}$ is the estimated standard deviation of the error term; and $tr(S)$ denotes traces of the cap matrix S. The cap matrix is a projection matrix of y observations with fitted values, where this cap is assigned to each row of the r_i matrix r_i.

$$r_i = X_i(X^T W_i X)^{-1} X^T W_i \tag{5}$$

Where X_i is the i-th row of the independent variable matrix X. The stages of research on the poverty level of districts/cities on the island of Java using the linear regression method and the first Geographically Weighted Regression are to conduct a descriptive analysis. Descriptive analysis was used to describe the distribution of poverty rates by districts and cities on Java Island in 2020, using the digital imaging software QGis. Then do the spatial effect test, which is carried out by the Breusch-Pagan (BP) test. If there is heteroscedasticity, it can be analyzed using the Geographically Weighted Regression (GWR) method. Modeling the poverty rate using the GWR method, finding the optimal bandwidth value based on cross-validation (CV) criteria. Define the weight matrix using the bisquare kernel function. GWR Model Parameters Estimation Using Optimal Bandwidth. The next step is to run a model fit test to see whether geographic factors influence poverty rates in Java. Perform subparameter significance tests to obtain significant variables for each district/city. The last step is to interpret the results of the model.

Results and Discussion

According to Figure 1, it is known that the Moran's index result is 0.355 where this value is greater than -1/n of -0.0084 where n is the number of regencies/cities in Java Island of 119 regencies/cities. These results indicate the occurrence of spatial autocorrelation, which means that

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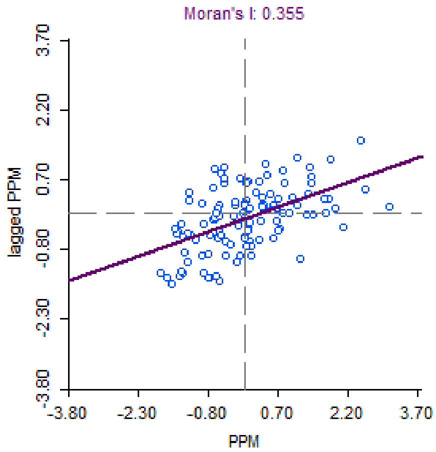
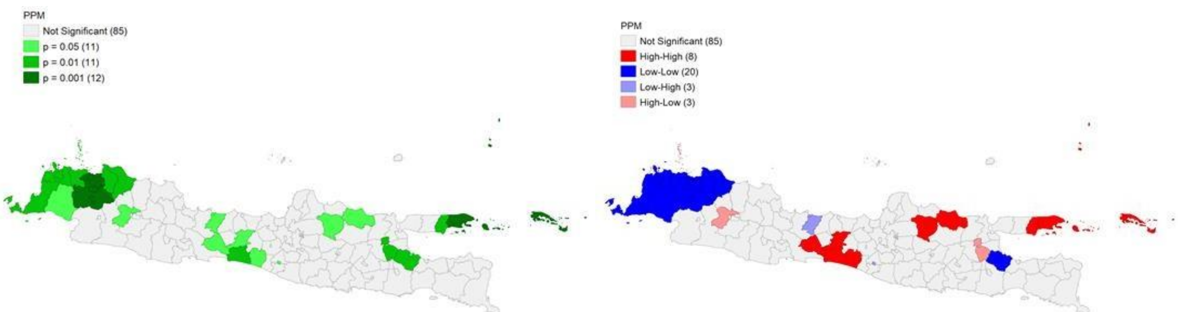
there is a spatial dependence of the poverty pattern of one district/city depending on other districts/cities. Moran's index is positive, meaning that poverty clusters occur in regencies/cities that have relatively the same poverty observation values and are located close to each other (Anselin, 1988).



Source: data processed

Figure 1. Scatter Plot Moran's Index

The distribution of spatial influences can be analyzed using the Local Indicators of Spatial Association (LISA) analysis technique. The LISA results are shown in Figure 2(a), that there is spatial autocorrelation in 34 districts/cities on Java Island with a significance of 0.001 to 0.05. In addition, there is a spatial clustering shown in Figure 2(b), namely there are 8 regencies/cities that are included in quadrant I (High-High), there are 3 regencies/cities that are included in quadrant II (Low-High), there are 20 regencies/cities the city is included in quadrant III (Low-Low), and there are 3 districts/cities including quadrant IV (High-Low).



(a) (b)

Source: data processed

Figure 2. (a) Spatial Significance of Poverty, (b) Spatial Autocorrelation of Poverty

The results of the Moran's and LISA index analysis have shown the pattern of poverty in Java but have not been able to determine the factors that influence poverty. The Geographically

Weighted Regression (GWR) method is used to see what factors affect the poverty of each district/city in Java Island.

Tabel 1. Global Regression Models

Variables	Coefficient
Constant	42.840 (10.930)***
OUR	-0.831 (-3.151)***
GRDP	0.003 (0.551)
CMW	-0.901 (-2.398)**
HDI	-0.383 (-6.798)***
Diagnostic Tools	
Adj R-Squared	0.534
AIC	589.961
F-stat	35.360***

Noted: *, **, *** significance at level 10%, 5% and 1% respectively

Tabel 1 that OUR, GRDP, CMW and HDI together have a significant effect on the percentage of poor people in Java at a significance level of 10%. While partially only TPT, UMK and HDI have a significant effect on the percentage of poor people in Java. The Global Model with the OLS method approach can explain the percentage of poor people of 53.4%, while 46.6% cannot be explained by the model. The results of the classical assumption test with global regression (OLS) show that the data are not normally distributed, non-multicollinear and heteroscedasticity occurs in the model, meaning that there is an unequal error variance in each observation area. Therefore, based on the previous description, each region cannot be assumed to be the same from an economic and social standpoint, and there is dependence between adjacent regions. Then the analysis is continued with Geographically Weighted Regression (GWR) analysis.

Tabel 2. Comparison of Adjusted R-Squared OLS and GWR Model

Model	Adjusted R-Squared
OLS Model	0.534
GWR Model (Adaptive Kernel Gaussian)	0.616

Source: data processed

The GWR model used in this study uses Kernel Gaussian adaptive weights. This weighting was chosen because there are regencies/cities in Java that do not intersect with other areas such as the Seribu Islands and Madura. Before carrying out an analysis of the factors that influence the proportion of poor people in Java, it is first compared with the coefficient of determination adjusted for the OLS and GWR models with Kernel Gaussian adaptive weights. Based on Table 2, the GWR model has $R^2{}_{adj}$ which is greater than the OLS model. So, the Gaussian Kernel adaptive GWR model is more appropriate for modeling the percentage of poor people in Java. The results of the analysis

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using GWR produce parameter values as many as regencies/cities in Java, namely 119 regencies/cities. The resulting regression equation model is as follows:

$$\widehat{PPM}_i = \beta_0(u_i, v_i) + \sum_{i=1}^{119} \beta_{1i}(u_i, v_i)OUR + \sum_{i=1}^{119} \beta_{2i}(u_i, v_i)GRDP_i + \sum_{i=1}^{119} \beta_{3i}(u_i, v_i)CMW_i + \sum_{i=1}^{119} \beta_{4i}(u_i, v_i)HDI_i + \varepsilon_i \quad (6)$$

Where PPM_i is the percentage of poor people in region i; OUR_i is the Open Unemployment Rate region i; ; $GRDP_i$ is the Gross Regional Domestic Product region i; CMW_i is the City Minimum Wage region i; HDI_i is the Human Development Index region i; u_i, v_i is latitude and longitude coordinates of the point on a geographic-i; β_{ik} (u_i, v_i) is the-k regression coefficient at each-i location; and ε_i is the error term. Then after analysis, the parameter estimates obtained from the GWR model are summarized in the table as follows:

Tabel 3. GWR Model Parameter Estimator

Estimator	Min	Q1	Med	Q3	Max	Mean	OLS
Constant	29.391	37.537	42.367	54.212	69.835	45.813	42.840
OUR	-0.640	-0.302	-0.168	0.103	0.540	-0.078	-0.831
GRDP	-0.025	-0.009	0.002	0.004	0.007	-0.002	0.003
CMW	-6.559	-1.628	-0.762	-0.483	-0.084	-1.561	-0.901
HDI	-0.867	-0.589	-0.352	-0.299	-0.222	-0.436	-0.383
Diagnostic Tools							
R-Squared				0.696			
Adjusted R-squared				0.615			
AIC				581.993			

Source: data processed

Table 3 there is a mean column which shows the average parameter estimator coefficients for each district/city in Java using the GWR model. It can be seen that there are differences in the coefficients for estimating the parameters of the two models, especially in the parameter estimators of the TPT, GRDP, and MSE variables, while the HDI is almost the same. In addition, it is necessary to test the significance of the GWR model, namely to see whether there are geographical factors or not in the case model, the percentage of poor people in Java. To answer the alternative hypothesis (Ha) the GWR model is better than the OLS model in explaining the percentage of poor people in Java, an ANOVA inference analysis was performed, the results of which are shown in table 4.

Tabel 4. GWR Model Significance Test (ANOVA)

Source	SS	df	MS	F-Stat
OLS Residuals	896.111	114		
GWR Improvement	286.984	19.848	14.459	
GWR Residuals	609.127	94.152	6.470	2.235*

Noted: *, **, *** significance at level 10%, 5% and 1% respectively

table 4, with a significance level of 10 percent the GWR model is better than the OLS model. So that the percentage of poor people in Java Island is better if it is explained by an explanatory variable with coefficients that vary geographically. Therefore, the GWR model provides different coefficients for each location, so the variables that have a significant effect on the percentage of poor people in Java can be seen in table 5 below.

Table 5. Significant Independent Variables in the GWR Model for Each Regency/City in Java Island

No	Regency/City	Significantly Influential Variables
1.	Jakarta Selatan, Jakarta Timur, Jakarta Pusat, Jakarta Barat, Jakarta Utara, Bogor, Sukabumi, Purwakarta, Karawang, Bekasi, Bogor, Sukabumi, Bekasi, Depok, Sragen, Grobogan, Blora, Rembang, Pati, Demak, Ponorogo, Trenggalek, Tulungagung, Blitar, Kediri, Malang, Lumajang, Jember, Banyuwangi, Bondowoso, Situbondo, Probolinggo, Pasuruan, Sidoarjo, Mojokerto, Jombang, Nganjuk, Madiun, Magetan, Ngawi, Bojonegoro, Tuban, Lamongan, Gresik, Bangkalan, Sampang, Pamekasan, Sumenep, Kediri, Blitar, Malang, Probolinggo, Pasuruan, Mojokerto, Madiun, Surabaya, Batu, Pandeglang, Lebak, Tangerang, Serang, Tangerang, Cilegon, Serang, Tangerang Selatan.	HDI
2.	Kepulauan Seribu, Karanganyar, Kudus, Jepara.	OUR and HDI
3.	Cianjur, Bandung, Garut, Tasikmalaya, Ciamis, Kuningan, Cirebon, Majalengka, Sumedang, Indramayu, Subang, Bandung Barat, Pangandaran, Bandung, Cirebon, Cimahi, Tasikmalaya, Banjar, Cilacap, Banyumas, Purbalingga, Banjarnegara, Kebumen, Purworejo, Wonosobo, Magelang, Boyolali, Klaten, Sukoharjo, Semarang, Temanggung, Kendal, Batang Pekalongan, Pemalang, Tegal, Brebes, Magelang, Surakarta, Salatiga, Semarang, Pekalongan, Tegal, Kulon Progo, Bantul, Sleman, Yogyakarta.	CMW and HDI
4.	Wonogiri, Gunung Kidul, Pacitan	OUR, CMW, and HDI

Source: data processed

Table 5, there are 65 regencies or cities in Java where the percentage of poor people is only significantly influenced by HDI; then there are 4 regencies or cities that are significantly influenced by OUR and HDI; 47 regencies or cities are significantly influenced by CMW and HDI; and 3 regencies or cities are significantly affected by OUR, CMW, and HDI. Then a classic assumption test was carried out on the GWR model. The results of the normality test for the residuals obtained a p-value of 0.323, so failing to reject H0 means that the normality assumption is fulfilled. And the GWR model can be used for future predictions. Based on Table 3, it is known that the average coefficient value of OUR is -0.831. This means that on average, an increase in the percentage of OUR can reduce the percentage of poor people by 0.831 percent. Then, based on Table 5, there are 7 districts or cities whose percentage of the poor population is significantly affected by OUR, and most of the percentages of poor people in districts or cities are not significantly affected by OUR. This result is in line with research by Loka & Purwanti (2022) which states that not all the unemployed are poor, or those who are unemployed are still being supported by people who have sufficient income.

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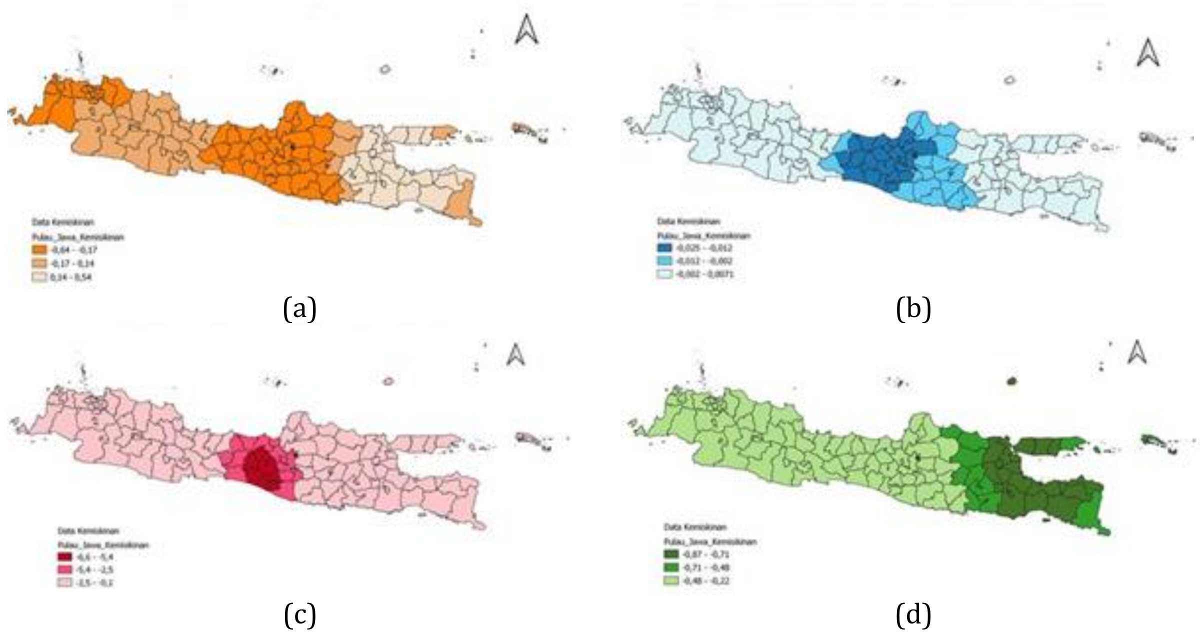
The GRDP does not significantly affect the percentage of poor people in all districts or cities. These results are consistent with research from Mulok et al (2012) which states that economic growth does not significantly reduce poverty because there is inequality in Indonesia. Since 1998, the economy has become less evenly distributed. So that the percentage of the poor population can be significantly reduced without economic growth that benefits the poor. CMW has a negative and significant effect on the percentage of poverty in 50 districts and cities on Java Island. The average coefficient value of CMW is -0.901, meaning that an average increase of 1 million rupiah in CMW will reduce the percentage of poor people by 0.901 percent. HDI significantly reduces the percentage of poor people in all districts or cities on the island of Java. The average coefficient value is -0.383, meaning that for every 1 point increase in HDI, the percentage of poor people will decrease by 0.383 percent. This result is in line with research by Lestari et al (2022) which states that the percentage of poor people increases when the HDI increases, which is an indication that an increase in HDI will increase work productivity and income generation. Increased income causes people to be able to meet their needs and reduce poverty levels.



Source: data processed

Figure 3. (a) OUR regression coefficient; (b) GRDP regression coefficient; (c) CMW regression coefficient; (d) HDI regression coefficient.

Figure 3 shows a map of the spatial diversity of factors that influence poverty in each district or city on Java Island. For each variable, the area that shows a darker color means that the area is very significantly influenced by the variable in question. Meanwhile, the brighter the color, the less it affects the percentage of poor people. For the OUR variable, it can be seen that the effect is most significant in some regions or cities in Banten, DKI Jakarta, Central Java, and the Special Region of Yogyakarta. Meanwhile, the CMW variable shows that the effect is most significant in some regencies and cities in Central Java and the Special Region of Yogyakarta. The HDI variable has the most significant effect on several districts and cities in East Java.

Conclusion

Based on this discussion, it shows that there is a spatial dependence of the poverty pattern of one district depending on other districts, as can be seen from the Moran's index of 0.356, and there is spatial clustering, namely 8 districts/cities included in quadrant I (High-High), there are 3 districts/cities included in the quadrant II (Low-High), there are 20 districts/cities included in quadrant III (Low-Low), and there are 3 districts/cities included in quadrant IV (High-Low). The GWR model with a Gaussian Kernel additive weight is better at explaining what factors affect poverty in Java compared to the OLS model with a value of R^2 = 0,615, where there are 65 districts/cities in Java Island only influenced by HDI, 4 districts/cities are influenced by OUR and HDI, 47 districts/cities are influenced by CMW and HDI, and 3 districts/cities are influenced by OUR, CMW and HDI.

Implication of the study that government as a policy maker based on the results obtained is that the government must be able to set a minimum wage policy (UMK) so that people can at least make ends meet and get out of the poverty trap. In addition, the government can provide job training so that more and more people work and will ultimately reduce the unemployment rate (TPT). Then to increase the HDI, the government can improve the quality of education and the level of public health services which will ultimately have an impact on reducing people's poverty. This research is still limited to several predictor variables in the form of the percentage of TPT, GRDP per capita, UMK, and HDI which are used in poverty modelling. In future studies it is recommended to use predictor variables in terms of education and health. Because these two factors greatly influence the quality of human resources, it is hoped that this will provide more information in explaining the level of poverty in the community, especially in Java.

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