JDEP Vol. 5 No. 1 (2022) hlm. 36-55

JDEP

Jurnal Dinamika Ekonomi Pembangunan

https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

SPATIAL ANALYSIS OF REGIONAL POVERTY IN CENTRAL JAVA INDONESIA

Aminuddin Anwar

Department of Economics, Universitas Islam Indonesia, Yogyakarta Indonesia

Abstract

This study analyzes the effect of the spatial interaction of poverty in districts/cities in Central Java for three periods, 2010, 2015, and 2019. The method used in this research is a spatial analysis using Global Moran's I Statistics, Local Indicator of Spatial Association (LISA), and spatial regression with the Spatial Autoregressive Model (SAR). Spatial distribution analysis concluded that the high concentration of poverty for three periods occurred in the southern part of Central Java, accompanied by a high concentration of unemployment and population. The results of the non-spatial regression analysis concluded that there was a negative effect of GRDP on poverty, a positive influence of population on poverty in Central Java for the three study periods, and a negative effect of education on poverty only in 2019. The estimation model uses SAR as the best model chosen to explain poverty conditions in Central Java, and it shows that poverty in neighbouring areas has a positive value, so it can be concluded that there is a spatial effect of poverty in Central Java. The spatial influence of poverty implies that the government carries out an integrated poverty alleviation program to produce policies that have local impacts in one area but must have a spatial impact, which means reducing poverty between regions.

Keywords: *Spatial Autoregressive Model, Regional Poverty, Economic Growth, Population*

JEL Classification: *R11, C21, I32.*

INTRODUCTION

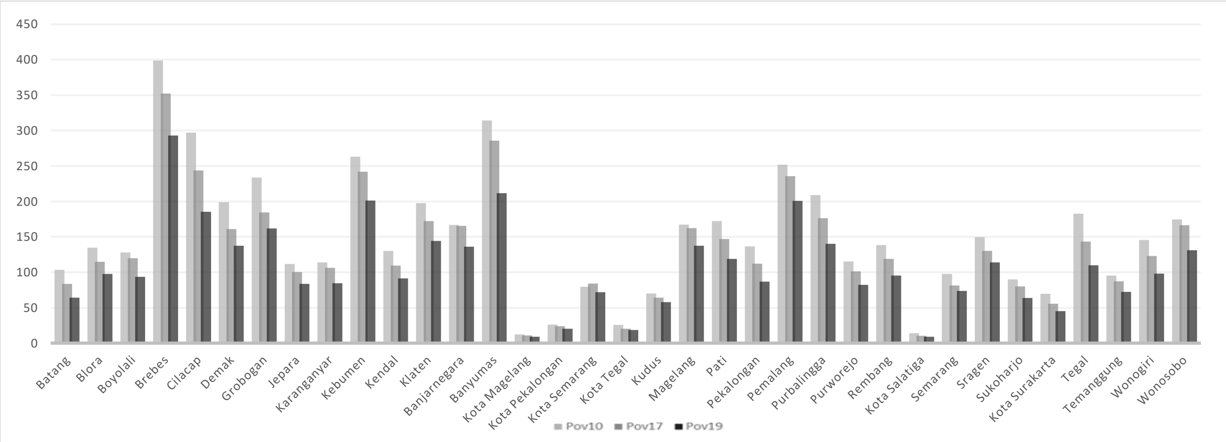
The main issue of development policy in developing countries such as Indonesia is inequality, which has implications for basic problems such as community welfare as indicated by poverty. According to (Hill, 1998), the condition of Indonesia has abundant resources, but inequality occurs in various matters such as education, health, and other social indicators. The problem of poverty faced by the government will have implications for the social and economic development of a region that further impact national conditions. The development of conditions in Indonesia (Yusuf & Sumner, 2015) in the administration of President Jokowi is indicated by a downward trend in the speed of economic growth and the poverty rate in Indonesia. This indication shows that the problem of poverty is still a major issue in economic development in Indonesia.

Analysis and studies related to regional issues in Indonesia, according to (Hill, 1998) are important to do because this regional policy orientation is aimed at regional development in Indonesia, so the identification of poverty problems is carried out by

JDEP Vol. 5 No. 1 (2022) hlm. 36-55
JDEP
Jurnal Dinamika Ekonomi Pembangunan
https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

the government on a macro and micro basis to obtain a comprehensive study related to solutions to poverty problems. Interaction and interconnection between regions are important aspects in regional studies, especially the problem of poverty which, according to (Rupasingha & Goetz, 2007), one of the main problems in poverty management is geographical variation and the concentration of poverty. What needs to be done by the government is to make policies based on the existence of regional interconnections that can effectively overcome the problem of poverty in the region. The government's effectiveness based on the analysis conducted by (Dartanto, 2013) is the existence of various approaches carried out by the government through integrated poverty alleviation policies and programs between sectors and regions so that the poverty alleviation process can occur for all regions.

Figure 1 Regional Poverty Levels in Regencies/Cities in Central Java in 2010, 2015 and 2019



Source: BPS (2021)

One of the islands in Indonesia that has an essential role in national economic development is Java Island because of the most extensive population distribution and the main centre of economic activity. Specifically, this study focuses on districts and cities in Central Java, one of the areas with the biggest poverty problem in Indonesia. Initial identification related to the development of regional poverty conditions in Central Java is shown in Figure 1. In general, the trend of poverty in the Central Java region shows a decline in the poverty rate for all regions in Central Java between the periods 2010, 2015, and 2019. Other things that can be analyzed from the condition districts in Central Java for the three periods are the concentration of poverty shown in specific areas such as the Southwest, Northwest, and Northeast of Central Java. This condition shows that policies related to poverty alleviation should be carried out by paying attention to spatial or regional aspects.

Based on regional conditions in Indonesia that tend to have disparities between regions and poverty groupings in Central Java Province, this study aims to implement a spatial model in regional poverty analysis in districts and cities in Central Java Province for three periods, 2010, 2015, and 2019. The development of a spatial model for poverty analysis was carried out at three points in time to analyze the development of a more dynamic poverty condition so that a comparison analysis between times could be carried out. The existence of an empirical study of the spatial model of poverty in districts and cities in Central Java is expected to have implications for the implementation of regional policies in Indonesia, especially studies related to regional poverty.

LITERATURE REVIEW

Fundamentally, issues and studies of poverty are problems faced by various countries in the world according to preliminary studies (Ravallion, 2001) related to economic growth, inequality, and poverty between countries. Another study by (Breunig & Majeed, 2020) shows the implications of inequality and poverty for a country's growth. This shows that poverty is one of the critical problems in the study of world economic development. One of the early studies related to poverty was shown by (Freeman, 2003) regarding the determinants of regional poverty in the United States of America with macroeconomic indicators as the determinant which shows that changes in unemployment income have implications for regional poverty conditions. Another study in Africa by (Gohou & Soumaré, 2012) which analyzed the relationship of Foreign Direct Investment (FDI) with poverty showed a decrease in poverty due to FDI flows. This initial study provides empirical evidence that the analysis of poverty determinants is an important part of regional studies in several countries.

Further studies related to regional poverty in Indonesia have been carried out to provide empirical evidence that economic and non-economic aspects have implications for regional poverty levels. Several early studies in Indonesia tend to be carried out to analyze the determinants of poverty without a spatial approach, namely (Balisacan, Pernia, & Asra, 2003) which analyzes the effect of economic growth on regional poverty in Indonesia and concludes that the welfare aspect is also an essential factor in reducing regional poverty. poverty in Indonesia before and after the financial crisis in Asia by (Suryahadi, Hadiwidjaja, & Sumarto, 2012) showed a downward trend in poverty reduction after the crisis. Development of another study conducted by (Dartanto, 2013) with a dynamic model in two time periods 2005 and 2007, in addition to another study by (De Silva & Sumarto, 2015) in districts and cities in Indonesia with a dynamic model for regional poverty analysis, and (Sriyana, 2018) with a panel model in Central Java on regional poverty reduction. The above study is a study related to regional poverty carried out in Indonesia, which shows that the formation of regional poverty is the economic sector and related to the non-economic sector but does not bring up spatial aspects in its analysis.

Further analysis in regional studies assumes that regions are not independent and that the interaction between regions happens revealed by (Gezici & Hewings, 2007) that the interaction between regions and the geographical location of an area has an important role in the economic performance of a region. The implementation of this was carried out (Chattopadhyay, Majumder, & Jaman, 2013) in India related to the socio-economic effect on poverty conditions carried out by decomposition and spatial analysis. Another study with a spatial approach was conducted by (Crandall & Weber, 2004) related to the socio-economic dimensions and concentration of poverty in the

United States, another study by (Voss, Long, Hammer, & Friedman, 2006) was also conducted in the United States analyzed the level of child poverty. Another study was conducted by (Amarasinghe, Samad, & Anputhas, 2005), which analyzed the spatial effects of poverty and food security in Sri Lanka. A study conducted by (Minot & Baulch, 2005) in Vietnam analyzed the geographic distribution of poverty. Other indicators such as social and political are also important determinants of poverty conditions in the United States (Rupasingha & Goetz, 2007). Another regional analysis by (Annim, Mariwah, & Sebu, 2012) in Ghana analyzes the spatial link between inequality and poverty. Some of these initial studies provide a perspective that regional linkages are an important aspect that needs to be considered in conducting studies on poverty. The conditions of regional differences and interactions between regions in regional economic studies are the initial motivation for conducting a more comprehensive study of aspects of regional poverty.

Studies conducted in Indonesia related to the implementation of spatial analysis are shown by (Daimon, 2001) who analyzes the spatial dimensions of welfare and poverty which concludes that there are spatial poverty traps between generations and explores that community empowerment policies are inappropriate policies to reduce poverty. Another study between regions in Jambi Province was conducted by (Nashwari, Rustiadi, Siregar, & Juanda, 2017) using Geographically Weighted Regression on the poverty model in farmer groups which showed that the road system and location were important aspects of poverty determinants. Another study that specifically implements spatial analysis in Java for poverty was carried out by (Aklilu Zewdie, 2015), who concluded that the main determinants of poverty in Java were education and unemployment.

The initial study of regional poverty analysis in Indonesia was analyzed by (De Silva & Sumarto, 2015) for regions in Indonesia but the analysis did not carry out spatial analysis in its study. Another study conducted by (Sriyana, 2018) specifically analyzed the conditions of poverty in Central Java but did not perform spatial analysis on the analysis model. A follow-up study conducted by (Nashwari, Rustiadi, Siregar, & Juanda, 2017) in Indonesia for the case in Jambi built a spatial model of poverty but used a Geographically Weighted Regression approach. Meanwhile, research by (Aklilu Zewdie, 2015) discusses spatial poverty that occurred in Java with cross-section data in the 2015 period. This study has differences from some of the earlier studies because it uses spatial analysis to analyze poverty with Spatial Autoregressive and Spatial Error models. A model in which research that examines poverty in Central Java (Sriyana, 2018) does not use this analysis. Another contribution of this research is to analyze from time to time using samples of more than one period, namely 2010, 2015, and 2019.

METHODOLOGY

The data used in this study is data at the district and city levels throughout the province of Central Java, namely 29 regencies and 6 municipalities. This study was conducted to analyze the condition of a point in time and compare it with conditions at another point in time. The time comparison analysis process used in this study is to analyze three-time points, namely 2010, 2015, and 2019, to see fundamental changes to the changing conditions that occur within that period. The data used in this study is secondary data obtained from the Central Statistics Agency (BPS) for the leading indicators of poverty and its determinants such as unemployment, population, GRDP, and the average length of schooling. Specifically, these variables can be explained in table 1.

Table 1 Definition of Variables

Variables	Symbol	Units	Definition
Poverty	Pov_i	Numbers of People	Number of poor people who are below the poverty line in each district/city in Central Java Province
Gross Regional Domestic Product	$GRDP_i$	Millions of Rupiah	The amount of added value produced by all business units in a certain area/region, or is the total value of final goods and services produced by all units of economic activity in a certain area/region in a certain period.
Unemployment	$Unmpl_i$	Percent	Percentage of the number of unemployed to the total labour force.
Education	$Educ_i$	Years	The number of years used by the population in undergoing formal education.
Population	*Popi*	Numbers of People	The number of residents or all people who live in a geographical area for 6 months or more and or those who live for less than 6 months but aim to settle down.

The analysis process is carried out through two main stages where in the first stage, a spatial distribution analysis is carried out to analyze the conditions of spatial relationship and concentration using Global Moran's I Statistics and Local Indicators of Spatial Association (LISA). The second stage is carried out by analyzing the effect of social and economic variables on poverty conditions by bringing up the spatial aspects of autoregressive and error for regression models based on spatial regression analysis.

Global Spatial Autocorrelation

The initial analysis step was carried out to detect spatial autocorrelation in the data with Moran's I statistics. Moran's I Statistics is used to detect and explain spatial groupings and can be decomposed into local statistical forms by providing graphic evidence of the existence of spatial groupings. To calculate this, Moran I Statistics and Moran Scatterplot (Anselin, 1988) and (Anselin, 1995) are used, namely:

$$I_i = \frac{n}{s} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum z_i^2} \qquad (1)$$

Based on the above formula, the value of n is the number of regions, z_i and z_j are the deviation values for the variables analyzed for each region, w_{ij} is the element of the weighting matrix with a value of 1 if i and j are neighbours and 0 if not. The value of Moran's I statistic with a value of 1 represents a substantial value and positive spatial autocorrelation, while if it is -1, it represents the condition of negative spatial autocorrelation.

Local Indicators of Spatial Autocorrelation

Further detection is carried out to identify local spatial patterns (Anselin, 1995) recommends measuring this with the Local Indicators of Spatial Association (LISA), a technique for decomposing values from global indicator values. According to (Anselin, 1995) the function of LISA is to identify local spatial clusters and can be used to diagnose local instability (spatial outliers). The value of LISA can be found using the following formula:

$$I_i = z_i \sum_i^n w_{ij} z_j \qquad (2)$$

Where the values z_i and z_j are the deviation values for the variables from the average analyzed for each region and the sum of these values until the value at j, n is the total number of geographic units or locations, w_{ij} is an element of the weighting matrix which is worth 1 if i and j are neighbors and 0 otherwise. Positive (negative) local spatial autocorrelation exists when we obtain positive (negative) values for I's and z-scores indicating the same (different) grouping of y values around location i.

Spatial Regression of Poverty

This study analyzes the effect of social and economic aspects on regional poverty conditions using a spatial approach. The application of the spatial model in this study is based on (Anselin, 1988) using two main approaches in spatial econometrics, namely the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM), wherein the analysis process of the best model will be chosen as a representation of the estimation results. The basic model of this study provides analysis without any spatial aspects of the model, namely:

$$\ln Pov_i = \beta_0 + \beta_1 \ln GRDP_i + \beta_2 Unmpl_i + \beta_3 ln\ Educ_i + \beta_4\ ln\ Pop_i + \varepsilon_i \qquad (3)$$

The development of the basic model above is carried out so that it can analyze the effects of poverty in neighbouring areas using the SAR model, namely:

$$\ln Pov_i = \beta_0 + \rho\ W\ Pov_j + \beta_1 ln\ GRDP_i + \beta_2 Unmpl_i + \beta_3 ln\ Educ_i + \beta_4\ ln\ Pop_i + \varepsilon_i \qquad (4)$$

The next model that is used to analyze the spatial aspect but in conditions of error, the SEM model is developed, namely:

$$\ln Pov_i = \beta_0 + \beta_1 \ln GRDP_i + \beta_2 Unmpl_i + \beta_3 ln\ Educ_i + \beta_4\ ln\ Pop_i + \varepsilon_i \qquad (5)$$

Where μ_i is the value of:

$$\mu_i = \lambda_1 W \mu_i + \varepsilon_i \qquad (6)$$

One of the fundamental aspects of the spatial model is the use of the spatial weight matrix, which is the essential tool used to model spatial dependencies between regions. Each region is connected to a set of neighbouring regions through a pure spatial pattern that is generated by exogenous conditions in the spatial weight matrix

W. This study uses the simplest form of the spatial weight matrix where an area is rated as 'neighbour' when they border part of each other (binary continuity matrix). According to the proximity criteria, the spatial weight matrix w_{ij} is one if the location is adjacent to the location and zero otherwise. For ease of interpretation, the spatial weighting matrix is standardized so that the sum of the values for the elements in a row is one. Based on the shape of the spatial weight matrix above, this study uses an *i x j* matrix where the shape and number of values in the cross-section is *35 x 35*.

The estimation process carried out on the econometric spatial model cannot be done using Ordinary Least Square (OLS) because the effect of neighbouring values on the model will have implications for the estimation process to provide a biased estimate value. The model estimation process begins with analyzing spatial autocorrelation, which is the initial requirement for a spatial relationship in the data. The next step is to test the data, namely normality using Jacques-Berra and Heteroscedasticity using Breusch-Pagan, to obtain good data conditions. The following process of spatial analysis is selecting the best model to choose the best model that can be interpreted based on this.

The process of selecting the model in this study uses the Lagrange Multiplier Test, which is a test of spatial interaction in cross-sectional conditions, further developed by (Burridge, 1980) and (Anselin, 1988) where the process of developing the LM test as a test of spatially dependent variables and errors in spatial correlation. Furthermore (Anselin, Bera, Florax, & Yoon, 1996) developed this method to test the autocorrelation spatial error of the dependent variable. In general, the LM test is a test to test one type of spatial dependence depending on another. The first step in selecting a model is to compare the results of the LM test lag and LM test error if one of the values is significant then the model is selected, but if the LM test value for both models is significant, then Robust LM test lag and LM test error are used to select the model that best (Anselin et al., 1996).

RESULT AND DISCUSSION

The initial step taken to analyze the condition of spatial poverty in districts and cities in Central Java is to analyze the spatial distribution in the form of Moran's I Statistics analysis and Local Indicator of Spatial Association (LISA). After getting the results of the spatial distribution, then proceed with doing a spatial regression analysis to analyze the effect of the neighbourhood on poverty in districts and cities in Central Java. The study results will be carried out to analyze three time periods, namely 2010, 2015, and 2019 so that the results of data analysis are obtained for each time point and compare the conditions for the three-time points.

Global Spatial Autocorrelation and Local Indicators of Spatial Autocorrelation

Moran's I Statistics results are shown in Table 2, which shows the statistical values for the variables used in the three-time periods. This result is a prerequisite for performing spatial regression analysis. Further analysis of Moran's I Statistics results is shown in Figure 2, which provides an overview of the regional distribution based on the spatial proximity of the variables used and their differences for each time point.

JDEP Vol. 5 No. 1 (2022) hlm. 36-55
JDEP
Jurnal Dinamika Ekonomi Pembangunan
https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

Table 2 Moran's Test I Statistics

Variables	2010			2015			2019		
	Val-I	Z	P-Val	Val-I	Z	P-Val	Val-I	Z	P-Val
Ln Poverty	0.131	1.555	0.060	0.134	1.593	0.056	0.123	1.483	0.069
Ln GRDP	0.105	1.300	0.097	0.107	1.315	0.094	0.110	1.344	0.089
Unemployment	0.150	1.711	0.044	0.304	3.170	0.001	0.463	4.682	0.000
Ln Education	0.136	1.569	0.058	0.187	2.048	0.020	0.222	2.379	0.009
Ln Population	0.068	0.956	0.170	0.066	0.944	0.173	0.066	0.936	0.175

Moran's I statistics in table 2 show that for the poverty variable in 2010, it was 0.131, in 2015 it was 0.134, and in 2019 it was 0.123 and significant at the 10 percent level, which indicates a positive spatial autocorrelation. Similar results are also shown by the GRDP variable, which shows that in 2010 it was 0.105, in 2015, it was 0.107, and in 2019 it was 0.110 and was significant at the level of 10 percent. For the unemployment variable, it is shown that in 2010 it was 0.150, in 2015, it was 0.304, and in 2019 it was 0.463 and was significant at the 5 percent level, indicating a positive spatial autocorrelation. In line with unemployment, the value of the education variable also shows a positive spatial autocorrelation with a value in 2010 of 0.136, in 2015 of 0.187, and in 2019 of 0.222, and significant at the 5 percent level. Different results are shown in the population variables, the results for the population variable show that values in 2010 it was 0.068, in 2015 it was 0.066, and in 2019 it was 0.066 but not significant at the 10 percent level. This indicates that there is no spatial autocorrelation for population variables so it implies that population conditions tend not to cluster in certain areas.

Based on the results of Moran's I Statistics, it can be concluded that the spatial relationship between the main variables used in this study is statistically proven and shows a positive spatial autocorrelation relationship. The results of positive spatial autocorrelation on poverty, GRDP, Unemployment, and Education indicate that there is a grouping between regions that have high-value conditions clustered in regions that have high conditions. On the other hand, conditions for areas with low conditions also cluster in areas with low conditions. This indicates that there is a high and low regional grouping for poverty, GRDP, Unemployment, and Education so that regions in Central Java have clusters for these variables.

This result shows a spatial grouping indicated by the grouping of high values in one area and small values in other areas. The Moran's Scatter plot results in Figure 2 become empirical evidence that shows the existence of spatial grouping. The results of the Moran Scatterplot for the poverty variable show that there is no change in the condition of the distribution of poverty between 2010, 2015 and 2019. The general condition of poverty shows that the grouping in the High-High area is 45.74 percent, High-Low is 25.71 percent, Low-High is 14.29 percent, and Low-Low by 14.29 percent. This result concludes that poverty clustering tends to occur in areas with high poverty scores.

The results of the GRDP variable show that the distribution pattern in three different periods does not change the distribution pattern as indicated by the distribution conditions in the High-High area of 37.14 percent, and High-Low of 8.57 percent, Low-High of 31.43 percent, and Low-Low. by 22.86 percent. In addition, the results for the education variable show the same conditions with no change in distribution conditions in the three periods. The distribution results show that the distribution in the High-High area is 25.71 percent, High-Low is 14.29 percent, Low-High is 17.14 percent, and Low-Low is 42.86 percent. In line with other variables, the population condition also has a relatively unchanged distribution for three periods, namely the High-High area of 60 percent, High-Low of 8.57 percent, Low-High of 25.71 percent, and Low-Low of 5.71 percent. GRDP, education, and population condition show that the distribution tends to remain unchanged for three periods and clusters in areas with low GRDP, low education, and high population.

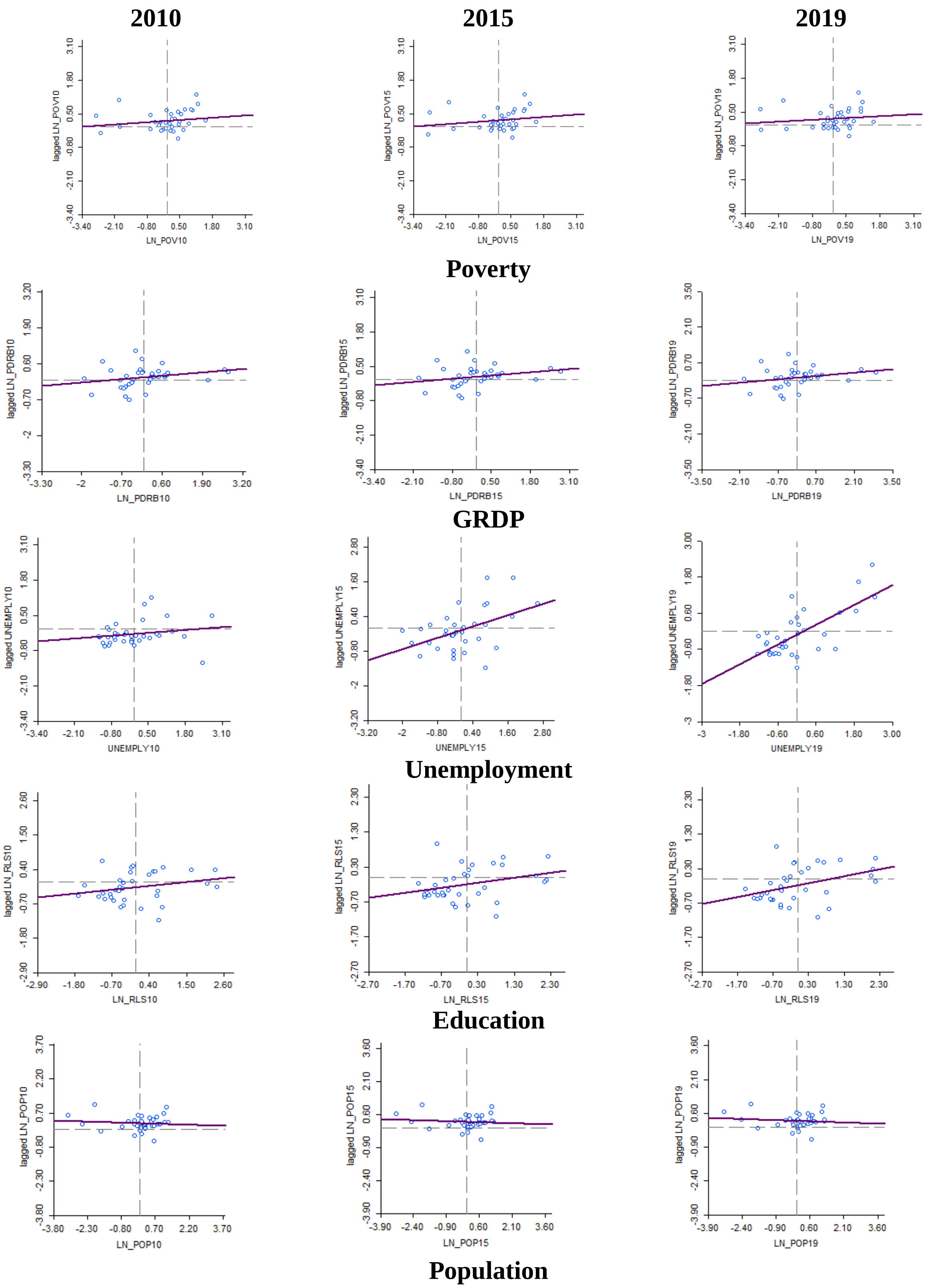
Different conditions occur in the unemployment variable, showing differences in distribution patterns between 2010, 2015, and 2019. The difference in distribution conditions for unemployment is shown in 2010 the distribution in the High-High area of 14.29 percent, High-Low of 25.71 percent, Low-High of 5.71 percent, and Low-Low by 54.29 percent. Distribution conditions for 2015 are indicated by the distribution conditions in the High-High area of 25.71 percent, High-Low of 20 percent, Low-High of 11.43 percent, and Low-Low of 42.86 percent. Conditions in 2019 showed that the distribution in the High-High area was 22.86 percent, High-Low was 11.43 percent, Low-High was 8.57 percent, and Low-Low was 57.14 percent. The results of the distribution of the unemployment variable indicate that the distribution of unemployment tends to cluster in areas with low unemployment.

The result of further analysis to map the spatial grouping conditions in this study was an analysis using LISA, showing a local grouping of conditions for each variable. Analysis using LISA was carried out to identify map-based output conditions showing several colour classifications, namely red, blue, light blue, and pink. The results of the red colour indicate that there is clustering for areas that have high conditions surrounded by areas that have high conditions, the blue colour indicates that there is a grouping for areas that have low conditions surrounded by areas that have low conditions, the light blue colour indicates that there is a grouping for areas with low conditions surrounded by areas with high conditions, and the pink colour indicates that there is clustering for areas with high conditions surrounded by areas with low conditions.

The results of the LISA in Figure 3 show the spatial concentration of poverty, GRDP, unemployment, education, and population. The results of the LISA for poverty show that the spatial concentration pattern for the three periods shows relatively little change in conditions. The conditions in 2010 were high concentrations of poverty in the Cilacap, Kebumen, Banjarnegara, Banyumas, Pemalang, and Purbalingga areas. Meanwhile, the low concentration areas were in the Tegal City area. Meanwhile, in 2015 high areas were shown in Cilacap, Kebumen, Banjarnegara, Banyumas, and Purbalingga areas, while low areas were shown in Purworejo and Tegal cities. In 2019, the high areas were shown by the Cilacap, Kebumen, Banyumas, and Purbalingga areas, and the low areas, it was shown by the Purworejo area and the City of Tegal.

JDEP Vol. 5 No. 1 (2022) hlm. 36-55
JDEP
Jurnal Dinamika Ekonomi Pembangunan
https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

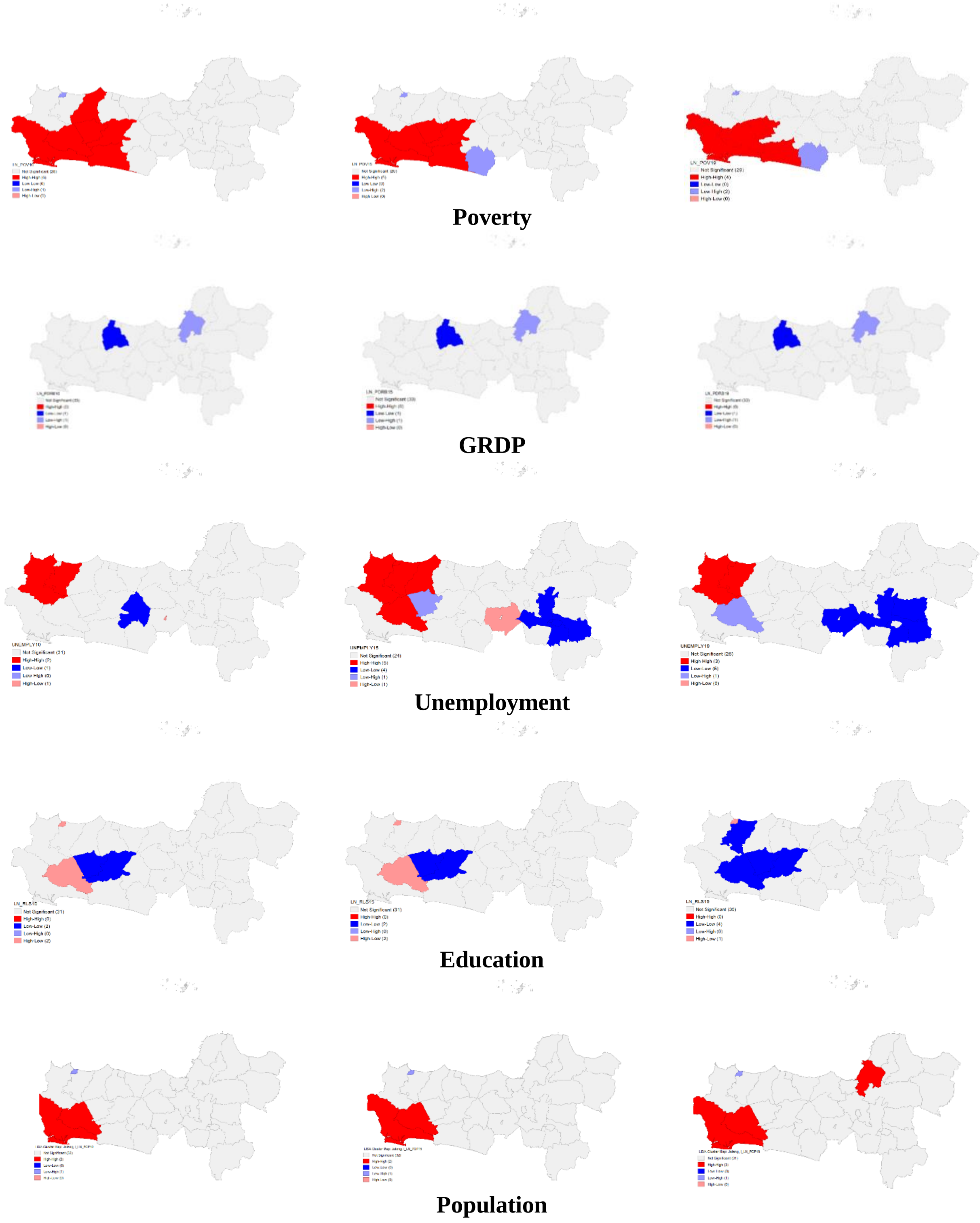
Figure 2 Results of Moran's I Statistics



JDEP Vol. 5 No. 1 (2022) hlm. 36-55
JDEP
Jurnal Dinamika Ekonomi Pembangunan
https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

Figure 3 LISA Results

2010 2015 2019



Unemployment conditions and population numbers for the LISA analysis show different conditions with the grouping between highly concentrated and low concentrated areas. Unemployment in 2010 showed a high concentration in the Tegal and Brebes areas, while for the low areas, it was shown by the Wonosobo area. In 2015 there was a change in the pattern of unemployment where areas with high concentrations were Tegal, City of Tegal, Brebes, Pemalang, and Banyumas, meanwhile for areas with low concentrations were Boyolali, Karanganyar, Sukoharjo, and Surakarta City. Unemployment conditions in 2019 also had changes where the high concentration of regions was Tegal, Tegal City, and Brebes, meanwhile for areas with low concentration were Boyolali, Karanganyar, Sukoharjo, Sragen, and Magelang. The same condition is shown from the LISA results for the population, which shows the same pattern in the 2010 and 2015 periods, where the highly concentrated areas are Cilacap and Banyumas while those with low concentration are Tegal City. The difference shown in the 2019 period is the addition of the Demak area which is included in the high category.

Different results for LISA are shown in the GRDP and Education variables which show that low conditions indicate the spatial concentration. The GRDP condition for the three periods did not change where the low condition tends to be shown from its distribution, which is in the Demak and Pekalongan areas. The results for the education variable in 2010 and 2015 did not show any change where the low regional concentration was shown by the Banjarnegara and Purbalingga areas, and the high area was the Banyumas area. Meanwhile, the condition of education for 2019 shows that the regional concentration is low in Banjarnegara, Purbalingga, Banyumas, and Tegal.

Based on the results of the spatial distribution for several main variables used in this study, it shows that the main conditions indicated by the presence of spatial concentration in Central Java are proven and are in line with previous research in Central Java conducted by (Caraka, 2018) which showed the occurrence of spatial autocorrelation. This is also supported by several follow-up studies from (Rupasingha & Goetz, 2007), showing that poverty conditions are not randomly distributed but have a systemic pattern. In addition, the spatial distribution pattern of poverty conditions in Indonesia is shown from the analysis (Pratama, Suparta, & Ciptawaty, 2021) in the Lampung area, which shows a concentration of poverty. Based on this, the concentrated condition of poverty in Central Java Province should be able to become the basis for policymaking by the government to consider regional aspects in terms of poverty policies.

Spatial Regression of Poverty

Further analysis was conducted to provide empirical evidence of the spatial relationship of poverty conditions in regencies and cities in Central Java by estimating the spatial model of poverty. The initial conditions shown through spatial distribution analysis using Global Moran's I Statistics and LISA indicate a spatial concentration of poverty so further analysis is needed in the form of spatial regression analysis. The process of data analysis with spatial regression is carried out in stages, starting with testing data specifications, and selecting models, where the output results of the process are shown in table 3.

Table 3 Model Specification Test

Specification Test	2010		2015		2019	
	Value	Prob	Value	Prob	Value	Prob
Normality Test (Jarque-Bera)	0.441	0.8019	1.551	0.4604	0.870	0.6473
Heteroskedasticity (Breusch-Pagan)	7.152	0.1281	2.124	0.7130	2.003	0.7353
Lagrange Multiplier (lag)	4.422	0.0355	6.187	0.0129	3.548	0.0596
Robust LM (lag)	5.139	0.0234	3.896	0.0484	2.628	0.1050
Lagrange Multiplier (error)	0.287	0.5924	2.302	0.1292	1.019	0.3128
Robust LM (error)	1.004	0.3165	0.011	0.9179	0.098	0.7541

The specification of the model that is carried out before estimating is to test for normality and heteroscedasticity. Based on table 3, the normality test results (Jarque-Bera) are shown by the probability value for 2010 of 0.8019, 2015 of 0.4604, and 2019 of 0.6473, where the probability value indicates that the data is normally distributed. The heteroscedasticity test (Breusch-Pagan) indicated by the probability value for 2010 of 0.1281, 2015 of 0.7130, and 2019 of 0.7353, so based on this value, the data can be concluded that the condition does not occur heteroscedasticity symptoms.

The next step to choose the best model is done by testing the model selection based on the specific to a general method, namely estimating the model with OLS, which is then tested using LM Test and Robust LM test for Lag and Error models. Table 3 for the model selection test shows that the probability value for LM Lag in 2010 is 0.0355, in 2015 is 0.0129, and in 2019 is 0.0596 which indicates that the value is significant at the 10 percent level. Meanwhile, the probability value for the LM error in 2010 is 0.5924, in 2015 it is 0.1292, and in 2019 it is 0.3128 which indicates that this value is not significant. Based on the LM lag and LM error results, it can be concluded that the best model in this study for the three periods is the SAR model.

JDEP Vol. 5 No. 1 (2022) hlm. 36-55
JDEP
Jurnal Dinamika Ekonomi Pembangunan
https://ejournal.undip.ac.id/index.php/dinamika_pembangunan/index

Table 4 Estimation Results

Variable	2010						2015						2019					
	OLS		SAR		SEM		OLS		SAR		SEM		OLS		SAR		SEM	
	Coeff	Prob	Coeff	Coeff	Prob	Coeff	Coeff	Prob	Coeff	Prob	Coeff	Prob	Coeff	Prob	Coeff	Prob	Coeff	Prob
Constant	- 6.873	0.0004	- 8.696	0.0000	- 6.628	0.0000	- 7.136	0.0003	- 9.384	0.0000	- 6.610	0.0000	- 5.810	0.0035	- 7.837	0.0000	- 5.514	0.0012
Ln GRDP	- 0.232	0.0951	- 0.267	0.0215	- 0.219	0.0677	- 0.263	0.0557	- 0.317	0.0045	- 0.234	0.0280	- 0.179	0.2130	- 0.261	0.0447	- 0.173	0.1498
Unemployment	- 0.001	0.9910	- 0.021	0.2533	- 0.003	0.8815	0.001	0.9794	- 0.025	0.3274	- 0.004	0.8705	- 0.008	0.7858	- 0.027	0.3496	- 0.005	0.8694
Ln Education	- 0.772	0.0782	- 0.516	0.1702	- 0.784	0.0458	- 0.800	0.0978	- 0.523	0.1954	- 0.834	0.0403	- 1.262	0.0269	- 0.921	0.0690	- 1.275	0.0093
Ln Population	1.244	0.0000	1.255	0.0000	1.213	0.0000	1.301	0.0000	1.366	0.0000	1.234	0.0000	1.162	0.0000	1.259	0.0000	1.135	0.0000
W Ln Poverty	-	-	0.385	0.0107	-	-	-	-	0.382	0.0114	-	-	-	-	0.317	0.0546	-	-
Lambda	-	-			0.214	0.4245	-	-	-	-	0.441	0.0542	-	-	-	-	0.303	0.1922
Observation	35		35		35		35		35		35		35		35		35	
R-Squared	0.9052		-		-		0.9073		-		-		0.9073		-		-	
Adjusted R-squared	0.8925		-		-		0.8949		-		-		0.8949		-		-	
Pseudo R-Squared	-		0.9187		0.9051				0.9175		0.9072				0.9175		0.9072	
Spatial Pseudo R-squared	-		0.9189		-				0.9142		-				0.9142		-	

The results of the analysis for 2010 show that the best model is the SAR model. Based on table 4, the estimation results show that there are non-spatial and spatial impacts on the poverty model in Central Java. Non-spatial conditions in the SAR model are indicated by internal factors, namely GRDP, Unemployment, Education, and Population. The estimation results show that GRDP has a coefficient of -0.267 with a probability of 0.0215, while the population has a coefficient of 1.255 with a probability of 0.000, which is significant at the 5 percent level. Different conditions are shown by Unemployment and Education which have insignificant values in this period. The results of the spatial effect in this model are shown from the neighbouring value for the poverty variable (W Ln Poverty), which shows a coefficient value of 0.385 with a probability of 0.0107, so it is significant at the 5 percent level, which means that there is an effect of poverty from neighbouring regions. The 2010 results show that poverty in Central Java is influenced by GRDP, and Population in its region and is influenced by poverty in neighbouring regions.

The results for 2015 in table 4 show that the best model is the SAR model. Based on the estimation of the model with SAR, it can be shown that the non-spatial impact on the model, namely GRDP has a coefficient value of -0.317 with a probability of 0.0045, and the population has a coefficient of 1.366 with a probability of 0.000, which means significant at the 5 percent level. Meanwhile, Unemployment and Education have insignificant values indicating that there is no effect on Poverty. The neighbour value indicates the results for the spatial impact for the poverty variable (W Ln Poverty), which shows a coefficient value of 0.382 with a probability of 0.0114, so it is significant at the 5 percent level, which means that there is an effect of poverty from neighbouring regions. The 2015 results show that poverty in Central Java is influenced by GRDP, and Population in its region and is influenced by poverty in neighbouring regions.

The conditions that occurred for 2019 in table 4 show that based on the SAR model for non-spatial effects on the model, namely GRDP has a coefficient value of -0.261 with a probability of 0.0447, and the population has a coefficient value of 1.259 with a probability of 0.000 which means significant at the 5 percent level. Meanwhile, the Education variable has a coefficient value of -0.921 with a probability of 0.0690, which means that it is significant at the 10 percent level. The results for unemployment show an insignificant value. The results for the spatial effect are shown by the neighbouring value of the poverty variable (W Ln Poverty), which shows a coefficient value of 0.317 with a probability of 0.0546 so that it is significant at the 10 percent level, which means that there is an effect of poverty from neighbouring regions. The 2019 results show that poverty in Central Java is influenced by GRDP, Education, and Population in its region and is influenced by poverty in neighbouring regions.

The results shown in non-spatial conditions are the negative influence of GRDP on poverty in Central Java for the three periods. This non-spatial result shows that the decline in the regional poverty rate in Central Java contributes to the increasing GRDP. This result is in line with what was stated by (Booth, 1997) that poverty reduction in Indonesia is the impact of sustainable economic growth. In line with this (Miranti, 2010) at the national level and (Erlando, Riyanto, & Masakazu, 2020) in the Eastern Region of Indonesia, the impact of economic growth on poverty will also have an impact on changes in inequality. The results of another study which also analyzed Regencies/Cities in Central Java (Sriyana, 2018) concluded the same thing the negative effect of economic growth on poverty. Based on these results, the government should be able to develop potential economic sectors to reduce regional poverty levels.

Another result shown from the non-spatial analysis is that there is a positive effect of population on poverty in Central Java, which positively impacts the three study periods. This condition shows that increasing population is to increase regional poverty due to the tendency of low population quality and increasing numbers tend to increase regional poverty. This result is different from those (Sriyana, 2018), which conclude that the population negatively impacts poverty reduction. Other studies (Miranti & Resosudarmo, 2005) also conclude that population does not affect poverty reduction in Indonesia.

The condition of education based on the results of the non-spatial analysis shows that in 2010 and 2015, there was no influence from education. Meanwhile, for 2019, education has a negative effect so the quality of the human model shown by the existence of good and increasing education will reduce regional poverty conditions in Central Java. This condition is in line with (Sriyana, 2018), which concludes that education has a negative effect on poverty in Central Java. Another study by (Dartanto, 2013) using microdata in Indonesia also proves the effect of education on poverty reduction.

The spatial analysis results for poverty in Central Java show that the neighbourliness aspect is proven to be one of the factors in determining regional poverty as indicated by the coefficient value in the spatial autoregressive model. This study indicates that for the three periods, a positive and significant value is obtained so that spatial interactions are proven to occur. This condition shows that the increasing poverty in neighbouring areas will increase poverty in other areas. The results of this study are in line with several previous studies conducted outside Indonesia, such as those (Rupasingha & Goetz, 2007) in the United States and (Želínský, 2014) in Europe. Other results in line with this study are (Nashwari et al., 2017) in Jambi Province and (Aklilu Zewdie, 2015) in Java. Based on these results, the government needs to formulate policies that are interrelated between regions in Central Java because of spatial concentration and overflow between regions. The government must be able to determine certain zones and central areas so that later the development of these areas will encourage other regions to grow.

CONCLUSION

Based on the analysis results using the spatial distribution of Global Moran's I and LISA, it shows that a high concentration of poverty occurs in the southern part of Central Java accompanied by a high concentration of unemployment and population. This condition shows that the spatial relationships related to several variables have interrelated conditions, where areas with high poverty rates are areas with high unemployment and low population.

The regression results shown in the three periods conclude that the non-spatial aspect is indicated by a negative relationship between GRDP and poverty for the three periods. This situation shows that the role of GRDP in reducing poverty in Central Java has proven to be happening so it needs to be a concern in policymaking by the government to increase regional economic growth rates. Another thing in the non-spatial aspect is the positive influence of the population on poverty for the three periods. The consequence of the influence of population in increasing poverty shows that the quality of people's lives must be improved because this can impact the existence of a quality population so that it can reduce poverty in the Central Java area.

The spatial aspect shown in the results of the spatial regression shows that the spatial aspect of poverty is proven. This is indicated by the spatial distribution that tends to clump together and the results of the spatial regression, which show that neighbouring areas have a positive effect on poverty in other regions for the three periods of poverty. Based on these results, it is evident that the spatial grouping of poverty will be followed by a spatial dependence that impacts regional poverty alleviation policies.

The spatial influence of poverty implies that the government carries out an integrated poverty alleviation program to produce policies that have local impacts in one area but must have a spatial impact, which means reducing poverty between regions. Policy implications that can be carried out by the Government due to the connectivity between regions in the problem of poverty are to carry out regional-based poverty alleviation programs where the government must prioritize areas that have a concentration of poverty in the western region of Central Java. Another policy that can be carried out by the government is to establish cooperation between districts and cities to solve poverty problems that arise due to the aspect of spatial linkages, which can be implemented in an integrated and collective poverty alleviation program between regions.

REFERENCE

Aklilu Zewdie, M. (2015). Spatial Econometric Model of Poverty in Java Island. *American Journal of Theoretical and Applied Statistics*, *4*(6), 420. https://doi.org/10.11648/j.ajtas.20150406.11

Amarasinghe, U., Samad, M., & Anputhas, M. (2005). Spatial clustering of rural poverty and food insecurity in Sri Lanka. *Food Policy*, *30*(5–6), 493–509. https://doi.org/10.1016/j.foodpol.2005.09.006

Annim, S. K., Mariwah, S., & Sebu, J. (2012). Spatial inequality and household poverty in Ghana. *Economic Systems*, *36*(4), 487–505. https://doi.org/10.1016/j.ecosys.2012.05.002

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers.

Anselin, L. (1995). Local Indicators of Spatial Association - Lisa. *Geographical Analysis*, *27*(2), 93–115.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104.

https://doi.org/10.1016/0166-0462(95)02111-6

Balisacan, A. M., Pernia, E. M., & Asra, A. (2003). Revisiting growth and poverty reduction in Indonesia: What do subnational data show? *Bulletin of Indonesian Economic Studies*, *39*(3), 329–351. https://doi.org/10.1080/0007491032000142782

Booth, A. (1997). Rapid economic growth and poverty decline: A comparison of Indonesia and Thailand 1981-1990. *Journal of International Development*, Vol. 9, pp. 169–187. https://doi.org/10.1002/(SICI)1099-1328(199703)9:2<169::AID-JID363>3.0.CO;2-G

Breunig, R., & Majeed, O. (2020). Inequality, poverty and economic growth. *International Economics*, *161*(September 2019), 83–99. https://doi.org/10.1016/j.inteco.2019.11.005

Burridge, P. (1980). On the Cliff-Ord Test for Spatial Correlation. *Journal of the Royal Statistical Society: Series B (Methodological)*, *42*(1), 107–108. https://doi.org/10.1111/j.2517-6161.1980.tb01108.x

Caraka, R. E. (2018). Analisis Kemiskinan Di Provinsi Jawa Tengah Dengan Pendekatan Spatial Autoregressive Model. *Jurnal Ekonomi Kuantitatif Terapan*, *11*(1), 53–60. https://doi.org/10.24843/jekt.2018.v11.i01.p04

Chattopadhyay, S., Majumder, A., & Jaman, H. (2013). Decomposition of inter-regional poverty gap in India: A spatial approach. *Empirical Economics*, *46*(1), 65–99. https://doi.org/10.1007/s00181-013-0683-8

Crandall, M. S., & Weber, B. A. (2004). Agricultural & Applied Economics Association Local Social and Economic Conditions , Spatial Concentrations of Poverty , and Poverty Dynamics. *American Journal of Agricultural Economics*, *86*(5), 1276–1281.

Daimon, T. (2001). The Spatial Dimension of Welfare and Poverty: Lessons from a Regional Targeting Programme in Indonesia. *Asian Economic Journal*, *15*(4), 345–367. https://doi.org/10.1111/1467-8381.00149

Dartanto, T. (2013). The determinants of poverty dynamics in Indonesia: evidence from panel data. *Bulletin of Indonesian Economic Studies*, *49*(1), 61–84. https://doi.org/10.1080/00074918.2013.772939

De Silva, I., & Sumarto, S. (2015). Dynamics of Growth, Poverty and Human Capital: Evidence From Indonesian Sub-National Data. *Journal of Economic Development*, *40*(2), 1–33.

Erlando, A., Riyanto, F. D., & Masakazu, S. (2020). Financial inclusion, economic growth, and poverty alleviation: evidence from eastern Indonesia. *Heliyon*, *6*(10), e05235. https://doi.org/10.1016/j.heliyon.2020.e05235

Freeman, D. G. (2003). Poverty and the macroeconomy: Estimates from U.S. regional data. *Contemporary Economic Policy*, *21*(3), 358–371.

https://doi.org/10.1093/cep/byg017

Gezici, F., & Hewings, G. J. D. (2007). Spatial Analysis of Regional Inequalities in Turkey Spatial Analysis of Regional Inequalities in Turkey. *European Planning Studies*, *15*(3), 383–403. https://doi.org/10.1080/09654310601017091

Gohou, G., & Soumaré, I. (2012). Does Foreign Direct Investment Reduce Poverty in Africa and are There Regional Differences? *World Development*, *40*(1), 75–95. https://doi.org/10.1016/j.worlddev.2011.05.014

Hill, H. (1998). The challenge of regional development in Indonesia. *Australian Journal of International Affairs*, *52*(1), 19–34. https://doi.org/10.1080/10357719808445235

Minot, N., & Baulch, B. (2005). Spatial patterns of poverty in Vietnam and their implications for policy. *Food Policy*, *30*(5–6), 461–475. https://doi.org/10.1016/j.foodpol.2005.09.002

Miranti, R. (2010). Poverty in Indonesia 1984-2002: The impact of growth and changes in inequality. *Bulletin of Indonesian Economic Studies*, *46*(1), 79–97. https://doi.org/10.1080/00074911003642252

Miranti, R., & Resosudarmo, B. (2005). Understanding Regional Poverty in Indonesia: Is Poverty Worse in the East than in the West? *Australasian Journal of Regional Studies*, (January).

Nashwari, I. P., Rustiadi, E., Siregar, H., & Juanda, B. (2017). Geographically weighted regression model for poverty analysis in jambi province. *Indonesian Journal of Geography*, *49*(1), 42–50. https://doi.org/10.22146/ijg.10571

Pratama, A. D., Suparta, I. W., & Ciptawaty, U. (2021). Spatial Autoregressive Model and Spatial Patterns of Poverty in Lampung Province. *EKO-REGIONAL*, *16*(1), 14–28.

Ravallion, M. (2001). Growth, inequality and poverty: Looking beyond averages. *World Development*, *29*(11), 1803–1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Rupasingha, A., & Goetz, S. J. (2007). Social and political forces as determinants of poverty: A spatial analysis. *Journal of Socio-Economics*, *36*(4), 650–671. https://doi.org/10.1016/j.socec.2006.12.021

Sriyana, J. (2018). Reducing Regional Poverty Rate in Central Java. *JEJAK: Jurnal Ekonomi Dan Kebijakan*, *11*(1), 1–11. https://doi.org/10.15294/jejak.v11i1.13272

Suryahadi, A., Hadiwidjaja, G., & Sumarto, S. (2012). Economic growth and poverty reduction in Indonesia before and after the Asian financial crisis. *Bulletin of Indonesian Economic Studies*, *48*(2), 209–227. https://doi.org/10.1080/00074918.2012.694155

Voss, P. R., Long, D. D., Hammer, R. B., & Friedman, S. (2006). County child poverty rates in the US: A spatial regression approach. *Population Research and Policy Review*, *25*(4), 369–391. https://doi.org/10.1007/s11113-006-9007-4

Yusuf, A. A., & Sumner, A. (2015). Growth, Poverty and Inequality under Jokowi. *Bulletin of Indonesian Economic Studies*, *51*(3), 323–348. https://doi.org/10.1080/00074918.2015.1110685

Želínský, T. (2014). Regional Poverty Levels in the European Union: A Spatial Econometric Approach. *Economy of Region*, *2*(3), 62–69.