Spatial Autoregressive Model and Spatial Patterns of Poverty in Lampung Province

By
Ahmad Dhea Pratama[*], I Wayan Suparta, Ukhti Ciptawaty
Faculty of Economics and Business, University of Lampung
[*]Corresponding Author: Ahmaddheapratama@gmail.com

ABSTRACT

Many research in economics only focus on the independence of a region while neglecting the effects of space and the interaction that occurs between mutually adjacent areas. The purpose of this study is to measure the multidimensional poverty concept in 15 districts/cities in the province of Lampung in 2015-2019. Spatial analysis such as moran i statistics, LISA clustered map, and lisa signification are used to analyze spatial patterns and spatial autocorrelation. Spatial modeling with spatial autoregressive model, geoda and geographical information systems are used as explanatory spatial data and spatial modeling. The results show that the percentage of poor people between districts/cities in Lampung Province have positive Moran's I values, there is a clustered pattern in 2015-2019, Moran scatter plot depicts 4 quadrants, LISA Cluster map indicates high-high and low-low areas, and LISA map has 4 significant areas. Spatial regression results show that per capita expenditure for nonfood has a negative effect, per capita expenditure for food has a positive effect, population growth rate has a positive effect, household clean water has a positive effect, life expectancy has a negative effect, mean years of schooling has a negative effect, and simultaneously the independent variables have a significant influence on the percentage of poor people. Poverty in Lampung Province is spatially related to each other between regions, the findings suggest that the variables used affect spatially. The implication of this result is one of the basis for inter-regional policies in the interests of multi-dimensional poverty alleviation between regions.

Keywords: Poverty, Spatial analysis, Spatial Autoregressive Model (SAR)

ABSTRAK

Banyak penelitian di bidang ekonomi hanya berfokus pada kemandirian suatu daerah dengan mengabaikan pengaruh ruang dan interaksi yang terjadi antar daerah yang saling berdekatan. Tujuan penelitian ini adalah mengukur Konsep kemiskinan multidimensi di 15 Kabupaten/kota di Provinsi Lampung tahun 2015-2019. Analisis spasial seperti statistic Moran I, LISA klaster map dan Lisa signifikasi, digunakan untuk menganalisis pola spasial dan autokorelasi spasial. Pemodelan dengan spasial autoregressive model, Geoda dan Sistem Informasi Geografis digunakan sebagai determinan data spasial dan pemodelan spasial. Hasil penelitian menunjukkan bahwa persentase penduduk miskin antar kabupaten/kota di Provinsi Lampung memiliki nilai moran i yang positif, terdapat pola bergerombol pada tahun 2015-2019, moran scatter plot menggambarkan 4 kuadran, peta klaster LISA menunjukan adanya daerah high-high dan daerah low-low, dan peta LISA menunjukkan 4 daerah signifikan. Hasil regresi spasial menunjukan bahwa pengeluaran perkapita untuk nonmakanan berpengaruh negatif, pengeluaran perkapita untuk makan berpengaruh positif, laju pertumbuhan penduduk berpengaruh positif, air bersih rumah tangga berpengaruh positif, angka harapan hidup berpengaruh negatif, rata-rata lama sekolah berpengaruh negatif dan secara simultan variabel bebas berpengaruh secara

signifikan terhadap persentase penduduk miskin. Kemiskinan di Provinsi Lampung secara spasial saling berkaitan antar wilayah, hasil temuan menyatakan bahwa varibel yang digunakan mempengaruhi secara spasial. implikasi hasil ini sebagai salah satu dasar kebijakan antar wilayah guna kepentingan peretasan kemiskinan yang multidimensi antar wilayah.

Kata Kunci: *Kemiskinan, Analisis Spasial, Spatial Autoregressive Model (SAR)*

INTRODUCTION

Poverty is a complex and multidimensional problem and cannot be seen easily from an absolute number. Poverty is the main development issue, especially in developing countries. The creation of welfare for the people is the ultimate goal of a country. Welfare is closely related to poverty. In theory, poverty is a situation when there is an inability to meet household needs such as food, drinking, shelter, clothing, education and health (Sukirno, 2010:44).

The problem of poverty has covered all aspects of the social, economic and environmental dimensions. Some researchers continue to solve the poverty paradigm that occurs with various spatial studies in the literature. Sen (1976) argues that the concept of poverty is not only a matter of income but also consists of various dimensions which together form the concept of poverty, in other words a person is not poor just because he does not have sufficient income to meet his needs, Instead because his chances of escaping poverty are reduced by lack of education, health and quality of life.

Research on multidimensional poverty from several studies was carried out spatially, for example Akinyemi & Bigirimana (2012) looks for patterns of poverty that emerged based on household living conditions in the city of Kigali in Rwanda. In addition, they seek contributions from four poverty indicators, namely: expenditure, health, education and services. For this purpose, they used data from the Integrated Living Survey of conditions between 2000-2001. In their findings, they show patterns of poverty and the existence of a urban-rural dichotomy. River, Vosti, and Maneta (2011) use city-level data to identify spatial patterns in rural areas of Brazil. Using the Moran's I indicator, they are able to identify "hot spots" and "cold spots", that is, areas where poverty is agglomerated or scattered, respectively. They found that there is evidence of clusters among municipalities and poverty reduction policies should be considered when the clusters are identified. However, these clusters are not bounded by state boundaries.

The paradigm of the spatial research model from several research findings shows that highly structured poverty continues to enter the root of regional hierarchies from urban to rural hierarchies causing the cycle of poverty to widen. Spatial aspects may have positive and negative effects on economic development and poverty. According to Kim (2008), poverty experienced by people who are in the trap of spatial poverty is likely to be characterized by multiple losses: low returns on all forms of investment, partial integration into fragmented markets, social and political exclusion and inadequate access to public services. They are more likely to be not only income poor (number of poor people) but also severely and chronically poor (poverty gap and duration of poverty), 'bad environmental effect' limits the opportunities of people living in the spatial poverty trap and limits their exit from poverty. That is, even if someone in the spatial poverty trap has entrepreneurial skills, investment capital and the willingness to invest in business, the return on their investment will be lower than in better connected areas with higher geographic capital and such environmental effects are undermined, and corporate success is more difficult to achieve. Adverse environmental effects extend their detrimental effects to investment in human capital as well. Parents investing in the education of their children in a spatial poverty trap tend to receive lower returns on investment.

Problem of poverty is still a serious agenda for every region in Indonesia. Each region has a different percentage level of poor people and the number of poor people, but still how many percent of that number indicates that the state has not created an equitable welfare and fulfilled their basic rights and needs. The demands of society for the government through services are of course very high because in accordance with Law Number 25 of 2009 concerning Public Services, the State is obliged to

serve every citizen and population in fulfilling basic rights and needs. This study focuses on an area on the island of Sumatra, namely the province of Lampung with the 3rd highest percentage of poor people among 10 provinces on the island of Sumatra.

The proportion of the percentage of poor people nationally is 10.16 percent. On the island of Sumatra, Aceh Province has a percentage of 16.03, Bengkulu 16.02, Lampung Province 13.14 and Sumatra South 13.12, these four provinces have the highest percentage among other provinces and higher than the national average, while the other 6 provinces have a smaller percentage than the national for the two provinces with the lowest percentage is Riau Kep of 5, 87 and Kep Bangka of 4.88 (BPS, Sumatra,2019). The difference in the level of development in developing the regional economy will have an impact on the differences in the level of welfare between regions.

The province of Lampung is often called the gateway to the island of Sumatra and is very close to the island of Java as the center of Indonesia's growth. Lampung Province administratively consists of thirteen regencies and two cities. The number and percentage of poor people in Lampung province based on data for the 2015-2019 period fluctuated from year to year, and have different levels of distribution dimensions between regions. The percentage of poor people in the Regency / City of Lampung Province, where the highest distribution level of the percentage of poor people covers 5 regions, namely North Lampung, East Lampung, South Lampung, Pesawaran and West Coast, with the regional distribution rate is 14.55% to 21.95%, while the lowest regional distribution pattern is in 5 regions, namely Bandar Lampung City, Metro City, Tulang Bawang Barat, Tulang Bawang and Mesuji 7.57% to 10.73 percent. In the spatial aspect the percentage of poor people is a phenomenon that can spread to neighboring areas (BPS, Lampung Province, 2020). According to Harmes et al (2018), poverty is influenced by location (space). The existence of the influence of location on poverty results in areas with high levels of poverty that will have an influence on the surrounding areas, allowing the formation of clusters of areas with the similar poverty levels.

SMERU (2008) conducted a Participatory Poverty Analysis (PPA) in three sub-districts of each study city (Surakarta city and Makassar city). These districts were selected by considering the distribution of geographic locations and variations in the typology of livelihoods. The PPA results reveal that spatial factors greatly influence the dynamics of poverty and vulnerability, as well as the livelihood characteristics of the urban poor. The spatial aspect of poverty is a description of the condition of the livelihood assets of the poor that are inadequate and do not support efforts to achieve sustainable livelihoods.

The pattern of spatial distribution and analysis of spatial modeling that reveals the problem of poverty is growing as understanding of the problem of poverty becomes more complex in various regions. Most of the concepts generally view poverty as a problem of an individual's inability to meet their basic needs, especially food. Other conditions that exist regarding poverty in economic development cannot be separated from several elements of human resources such as population growth rate, education and health levels which are part of the scope of this study. According to Bird et al. (2010), the agroecological characteristics of an area can affect the ability of its inhabitants to meet their basic needs, most of the national household survey data shows that significant regional dimensions of poverty incidence spatial poverty traps can be found even when a country has experienced economic growth and aggregate poverty reduction. So if reducing poverty, overcoming chronic poverty and facilitating more equitable growth are the desired outcomes then understanding and addressing this geographic dimension of poverty is essential.

Many economists focus on the independence of a region, so they forget to consider the spatial influence and interactions that occur between one region and its region. Poverty is not an individual problem, but a multidimensional challenge that must be resolved from various aspects. It cannot be denied that the economic diversity and the diversity of welfare levels between regions will get regional analysis in a spatial pattern.

METHODS

This study analyzes quantitative descriptive and uses a geographic information system with a Geoda analyzing tool spatially. The data used is secondary data, with a cross-sectional data panel of 15

districts and cities with a time series of 2015-2019. The data used comes from the Central Statistics Agency of Lampung province in every 15 districts/cities and poverty information data book of districts and cities in Indonesia.

Table 1. The Operational Definition and Description of Research Variables

No	Variabel	Symbol	Unit	Explanation
1.	Percentage of Poor People	Y	Percentage	The figures shown by HCI-P0 show the proportion of poor people in a region.
2.	per capita expenditure for non-food	PENF	Rupiah	Average Consumption for non-food
3.	per capita expenditure for food	PEF	Rupiah	Consumption of an area expended for food
4.	Population Growth Rate	PGR	Percentage	Figures showing the rate of increase in the population per year in a certain period of time. This figure is expressed as a percentage of the basic population.
5.	Percentage of poor households using clean water	PCW	Percentage	Poor households that use the main source of drinking water from unsustainable water (rainwater), protected or unprotected water, provided that the source of bathing / washing / etc, comes from protected water.
6.	Life expectancy	LE	Percentage	Estimates of the average length of life of the population assuming no change in the pattern of mortality by age.
7.	Mean Years of Schooling	MYS	Percentage	Average length of schooling for residents aged 15 years and over.

Hypothetical framework in the concept of spatial models
Spatial regression is the result of the development of the classical linear regression method. The development is based on the influence of place or spatial on the analyzed data, a spatial model that involves spatial influence is called a spatial regression model. One of the spatial effects is spatial autocorrelation. The presence of spatial autocorrelation causes the formation of autoregressive spatial parameters and moving averages, thus forming a spatial process by Anselin (1998). Based on the type of data, spatial modeling can be divided into modeling with a point and area approach. This study uses an area approach including Mixed Regressive-Autoregressive or Spatial Autoregressive Models (SAR), Spatial Error Models (SEM), Spatial Autoregressive Moving Average (SARMA), and panel data. Spatial modeling is very close to the autoregressive process, indicated by the dependence relationship between a set of observations or locations. The relationship can also be expressed by the value of a location depending on the value of the other location which is adjacent or neighboring.

Figure 1. Framework for Spatial Regression Decision Making Process.
Source: Anselin (1998)

Spatial data analysis is a data analysis to obtain observational information that is influenced by the space or location. Spatial regression is used to determine the factors that affect the dependent variable by considering spatial interactions.

Analysis To Measure Spatial Interrelationships (Spatial Autocorrelation)
Spatial Pattern Analysis
Spatial pattern of poverty in this study is analyzed using global moran index and anselin local moran. Spatial autocorrelation using global moran index is measured with the following formula:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{n}(x_i - \bar{x})}$$

Where x is the average observation and W_{ij} the linkage between regions i and j. In testing the Moran I Index output, the hypothesis can be used as follows, H_0 was rejected at the time of $-Z(I) < -1.645$. If the value of $Z(I) >$ of $Z\alpha/2$ or $-Z(I) < -Z\alpha/2$ then it can be concluded that there is a significant regional linkage at the level of α significance. The range of values of the Moran Index in the case of a standardized spatial weighting matrix is $-1 \le I \le 1$. Value $-1 \le I < 0$ indicates the presence of negative spatial autocorrelation, while the value $0 < I \le 1$ indicates the presence of positive spatial autocorrelation, the zero-value Moran Index value indicates ungrouped. Spatial autocorrelation is the correlation between variables and themselves based on space or can be said the similarity of objects in a space, whether distance, time or region. The amount of spatial autocorrelation can be used to identify spatial relationships (Anselin 1998). For spatial autocorrelation measurement can be calculated using Moran Index with the following formula:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(xi - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(xi - \bar{x})^2}$$

Where:
I   = Moran Index
n   = Number of locations

Xi = Value in location i
Xj = Value at location j
x = Average value of (xi) of n locations
wij = Elements on weighting are standardized between i and j.

The value moran I is equal to the correlation coefficient of -1 to 1. A high value means that the correlation is high, while the value 0 means the absence of autocorrelation. However, to say there is or is no autocorrelation is necessary compared to statistical value I with the value of expectations. The expected value of I is:

$$E(I) \quad \frac{-1}{(n-1)}$$

The Moran Index is widely used to measure global spatial autocorrelation and for local spatial autocorrelation testing can be used the LISA Index which identifies how the relationship between an observation location to another observation location (Jay et al. 2001). test statistics used are derived from the standard normal spread, namely:

$$Z(I) \quad \frac{I-E(I)}{\sqrt{Var(I)}} \sim N(0,1)$$

Where:
I = Moran index
Z(I) = Moran index test statistical value
E(I) = The expected value of the Moran index

If Z(I) > Z1-α H0 is rejected (there is a positive spatial autocorrelation). The numerical scale range of the Moran Index used to see the presence of spatial autocorrelation as seen in the table (Jay et al. 2001)

Table 2. Moran Index Scale

No	Description	Moran i
1	Cluster/group patterns with adjacent dots show the same characteristics (positive spatial autocorrelation)	I > E(I)
2	Random pattern or no specific pattern indicated by dots based on characteristics	I = E(I)
3	Negative spatial autocorrelation, with adjacent dots showing different characteristics	I < E(I)

Source: (Jay et al. 2001)

The autocorrelation test in this study used Spatial Autocorrelation (Moran Index) analysis tool from Geoda software. The tool calculates spatial autocorrelation based on the attribute values and location of each sub-district. From these attribute values and locations, the tool will present the output of the Moran Index value and the pattern formed whether it is clustered, random, or dispersed.

Anselin local moran analysis
The explanation of formulas and tables in the previous point is to calculate the Global Moran Index. Another tool is needed to detect local indicators of spatial association (LISA). The tool used is the Local Moran Index Lisa analysis requirement there are two, namely, LISA for each observation indicates a significant spatial grouping around the observation area, the addition of LISA for all observations is proportional to the indicator of global spatial linkage. The purpose of LISA is to identify spatial groupings and outliers. The formulation of the Local Moran Index is as follows:

$$I_i = \frac{(X_i - \bar{X})\sum_{j=1}^{N} w_{i,j}(X_j - \bar{X})}{\sum_{i=1}^{N}(X_i - \bar{X})^2/n}$$

Where :
Ii   = Moran Index region i
Wij   = Spatial weighing element that refers to the location of region i to neighboring areas j
X   = average
Xi   = Value of regional observation variable i
Xj   = Area observation variable value j

If the value Ii is positive and significant then the grouping of regions occurring around region i is a grouping of regions that have the same characteristics as region j. Conversely, the value ii negative and significant then the grouping of regions that occur around the region i is a grouping of regions that have different characteristics with the region j (Anselin 1995).

Local Indicator of Spasial Association (LISA)
Local Indicator of Spatial Association (LISA) is a statistic used to find out the specific relation of the region. (Anselin 1995), suggested LISA should meet two requirements: LISA for each observation indicates a significant spatial grouping around observations, the sum of LISA in each local size for all observations proportional to global size. The purpose of LISA is to identify local groupings that are outlierspatial. The formulation of the Local Moran Index is as follows:

$$I_i = \frac{(Y_i - \bar{Y})\sum_{j=1}^{N} w_{ij}\left(Y_j - \bar{Y}\right)}{\sum_{i=1}^{N}(Y_j - \bar{Y})^2/N}$$

If the value i_i is positive and significant then the grouping of regions that occur around region I is a grouping of regions that have the same characteristics as region i. Conversely, the value i_i negative and significant then the grouping of regions that occur around region I is a grouping of regions that have different characteristics with region i.

The moran scatterplot
Moran scatterplot is a tool used to look at the relationship between standardized observation values and the average values of standardized neighbors. Mapping using Moran scatterplot will present four quadrants that describe the four types of relationships of a region with other surrounding areas as neighbors (Anselin 1995)

Quadrant I *High-High*	Quadrant IV *High-Low*
Quadrant II *Low-High*	Quadrant III *Low-Low*

Source: Geoda, 2021

Zhukov (2010) explains the division of the quadrants in the Moran Scatterplot as a level of observed area values as follows:
  a. In quadrant I, HH (High-High) shows that areas that have high observational value are surrounded by areas that have high observational values.
  b. In quadrant II, LH (Low-High) shows that areas with low observational values are surrounded by areas that have high observational values.
  c. In quadrant III, LL (Low-low) shows that areas that have low observation values are surrounded by areas that have low observation values.
  d. In quadrant IV, HL (High-Low) shows that areas with high observational values are surrounded by areas that have low observational values.

Value I and I_0 and quadrant divisions in a region can be seen through Moran's Scatter Plot Index. Scatter Plot Moran's Index is a diagram to see the relationship between the value of a location (standardized) and the average of the value of the locations that are related to the location in question (Jay et al. 2001). On Moran's Index test the hypothesis was carried out as follows:

H_0 :I = 0 (no autocorrelation between locations)

H_a :I ≠ 0 (there is autocorrelation between locations)

Modeling With The Concept Of Spatial Regression
Model Autoregressive Spasial (SAR)
Anselin (1998), describe the Spatial Aggressive Model (SAR) in the equation If ρ ≠ 0 and λ ≠ 0, then the equation becomes:

$$y = \rho WY + XB + \varepsilon$$
$$\varepsilon \sim N (0, o^2 I)$$

Where:

y : vector dependent variable

ρ : spatial autocorrelation coefficient parameter on dependent variable

W : weighting matrix

β : vector coefficient of regression parameters

X : independent variable matrix

ε : vector error

The hypotheses used in significant autoregressive spatial regression tests are as follows:

H0 : ρ = 0 (Insignificant parameter)

Ha : ρ ≠ 0 (Significant parameters)

Spatial Error Model (SEM)
Describe the Spatial Error Model (SEM) in the equation If ρ = 0 and λ ≠ 0 , then the equation becomes:

$$y = XB + \lambda Wu + \varepsilon$$
$$u: \lambda Wu + \varepsilon, \text{ With } \varepsilon \sim N (0, o^2 I)$$

Where:

y : vector dependent variable

X : independent variable matrix

β : vector coefficient of regression parameters

λ : parameter coefficient of spatial coefficient error

ε : vector error

W : weighting matrix

The hypothesis used in the significant test of spatial regression error is as Following:

H0 : λ = 0 (Insignificant parameter)

Ha : λ ≠ 0 (Significant parameters)

Lagrange Multiplier Test (LM)
Spatial effect that is spatial dependency occurs due to correlation between regions. Spatial dependency effects, namely lag dependency and spatial residuals can be tested using the LM test. The results obtained from the LM test will be used as the basis for the formation of spatial regression models. Methods used to select the best model by using values Log Likelihood (LL), Akaike Info Criterion (AIC) and Coefficient of Determination (R2) (Widarjono, 2007). However, in principle to determine which model more precisely describe an observational data should be returned to the theory underlying problems (Anselin 2010)

RESULTS AND DISCUSSIONS

Spatial autocorrelation proportion the percentage of poor population of 15 regencies/cities in Lampung Province

The Moran I results for all percentages of poor people in the entire research period from 2015-2019 can be seen at Table 3:

Table 3. Moran'I Percentage of Poor People in 15 Regencies/Cities in Lampung Province 2015-2019

Year	Moran's I	E(I)	Z-Value
2015	0.0081	-0.0714	0.4687
2016	0.0353	-0.0714	0.7196
2017	0.0359	-0.0714	0.7192
2018	-0.0018	-0.0714	0.4789
2019	-0.0089	-0.0714	0.4332

Source: Processed, Open Geoda, 2021

The Moran I value in 2015, 2016, 2017 has positive autocorrelation value and has spatial association in the form of grouping in the percentage of poor population. The years 2018 and 2019 have negative autocorrelation values and have a pattern of percentage of poor people with different characteristics. From the results of research on spatial linkages of the percentage of poor people between Districts/cities in Lampung Province in 2015-2019, the value of Moran's is 0.264524. This indicates that there is a spatial linkage in the form of positive autocorrelation which means the number of poor populations between districts / cities in Lampung Province there is a clustered pattern of regions with the same characteristics. To see if there is a statistically significant spatial linkage, a Z test is performed. If the Z value is greater than $Z_{\alpha/2}$ or less than $-Z_{\alpha/2}$ then it can be concluded that there is a significant regional linkage at the level of α. In this study, the critical α was 5% or $Z_{0.95}$ = 1.654 Overall $Z(I) > Z_{0.95}$ is 2.232 > 1.654 which means there is a statistically significant spatial linkage of the percentage of poor people.

In the 2015-2019 poor population percentage Moran scatter plot shows the distribution pattern divided into 4 parts namely high-high, low-high, low-low and High-low areas Spatial pattern analysis to detect the local grouping of the Percentage of Poor People in 15 Districts/Cities in Lampung Province by analyzing the distribution pattern of thematic map output processed with Geoda following Moran's scatter plot:
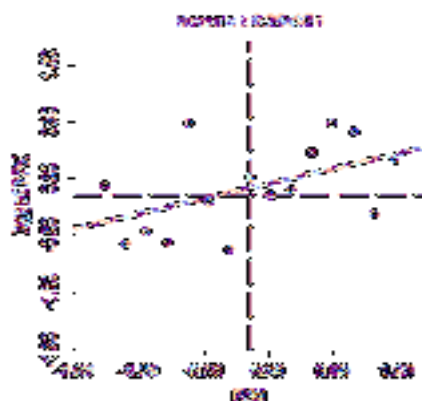

Figure 2. Moran's Scatterplot depicting the pattern of Population in 15 Regencies/Cities in Lampung Province
Source: Processed, Open Geoda, 2021

The Moran I quadrant of the Percentage of Poor Population explains, in quadrant I: HH (High-High) covers the areas of East Lampung, Central Lampung, North Lampung, Way Kanan, Mesuji, Tulang Bawang, Tulang Bawang Barat, In quadrant II: LH (Low- High) covers the area of Metro city, Bandar

Lampung City, in quadrant III: LL (Low-Low) covers areas, West Lampung, West Coast, Tanggamus, Pesawaran, Pringsewu and in Quadrant IV: HL (High-Low) covers the South Lampung area. The next result is a mapping with the LISA Cluster Map Results in Figure:
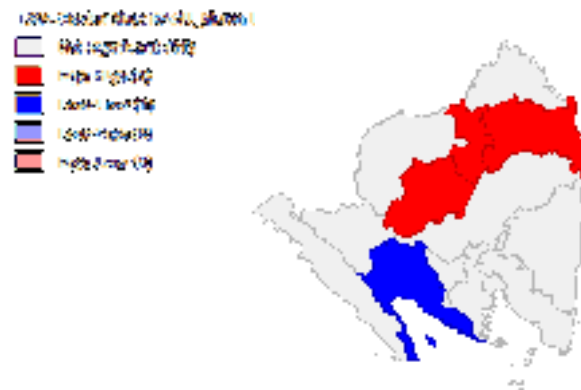

Figure 2. Lisa Clusterd Map of Poor People in 15 Regencies/Cities in Lampung Province
Source: Open Geoda, 2021

LISA Cluster map illustrates the grouping on the Percentage of Poor People with indications of High-high areas covering 3 areas namely West Tulang Bawang, Tulang bawang and North Lampung while for low-low grouping areas indicate 1 area namely Tanggamus. Next we will look at the level of signification in the area with Lisa Significance map Here is an analysis of lisa signification distribution map in Figure:
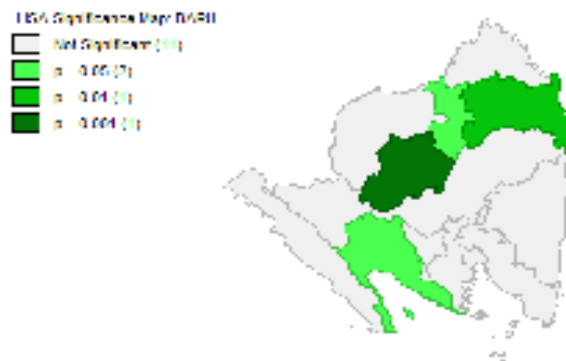
Figure 3. Lisa Map Significant Percentage of Poor People in 15 Regencies/Cities in Lampung Province
Source: Open Geoda, 2021

LISA signification map on signification 0.05 has 2 areas namely west Tulang Bawang and Tanggamus, signification 0.01 namely Tulang Bawang area and 0.001 signification rate that is North Lampung area. The difference in the percentage of poor people in each district/city will cause the grouping or dissemination of neighborly relationships to play a role in how the region affects its neighbors.

Spatial Autoregressive Model (SAR) in Poverty in 15 Districts / Cities in Lampung Province
Lagrange Multiplier (LM)
The choice of spatial model is done by using Lagrange Multiplier (LM) as initial identification. Lagrange Multiplier (LM) is used to detect spatial effects more specifically by using lag, error or both (lag and error). The spatial relationship test was carried out on the weight of queen contiguity. The results of the Lagrange Multiplier (LM) test in table 4 are as follows:

Table 4. Lagrange Multiplier (LM) Results

Test Spatial Dependencies	Value	P-value
Moran'l (*error*)	3.1448	0.00166
Lagrange Multiplier (lag)	9.1900	0.00243
Lagrange Multiplier (*error*)	2.1656	0.14113
Lagrange Multiplier (SARMA)	10.7214	0.00470

Source: Geoda Regression estimated spatial data processed,2021

The LM test concludes that the SAR modeling rejects H0 because the p-value (0.00243) <α = 0.05, with the LM Robust value 0.00344, so there is a spatial dependence on the model, so it is necessary to form a spatial model used is Spatial Autoregressive Model (SAR). Further testing with a comparison of the classical regression model and spatial regression, here are the results of the model comparison:

Table 5. Comparison of Classic Regression Models and Spatial Regression Models

Koefisien	OLS	SAR	SEM
R2	0.78665	0.96698	0.92846
AIC	79.2966	59.1517	68.9265
Log Likelihood	-31.6483	-20.5759	-26.4632

Source: Geoda Regression estimated spatial data processed,2021

Table 5. Shows the AIC value at SAR of 59.1517 with a Log Likelihood value of -20.5759 and R2 0.966983 this value shows that the Spatial SAR Model is better than other spatial models. The SAR model was chosen to analyze cases of spatial association. Following are the results of the Spatial Autoregressive Model estimation.

Table 6. Spatial Autoregressive Model (SAR) Regression Estimation Results

Variable	Coefficient	Std.Error	Z-Value	P-value
CONSTANT	7.10204	4.72789	1.50216	0.13306
ρ	0.91912	0.05163	17.8005	0.00000
PENF	-0.25593	0.07610	-3.36282	0.00077
PEF	0.06618	0.01729	3.82752	0.00013
PGR	20.0523	2.28959	8.75804	0.00000
PCW	-7.56219	2.3964	-3.15565	0.00160
LE	-4.88184	1.31733	-3.70586	0.00021
MYS	-5.89744	1.43897	-4.09838	0.00004

R2 = 0.966983
Log likelihood := -20.5759
Akaike Info Criterion =59.1517
Signifikasi $\alpha = 0.05$

Source: Geoda Regression estimated spatial data processed,2021

Based on the estimated calculation obtained by R^2 of 0.966983, the model is able to interpret the percentage of influence of all independent variables on the dependent variable by 96% and the remaining 4% by other variables not included in the research model. Spatial modeling of SAR has a significant spatial lag coefficient (ρ), which means that there is a dependency on the lag between regions. The value of ρ obtained was 0.91912, which means that the amount of spatial interaction between districts / cities and other regencies / cities in Lampung province which has similar characteristics is 0.91912. The following is the mathematical modeling of the Spatial lag model:

$$\hat{y}_i = 0{,}91912 \sum_{i=1,i\neq j}^{n} w_{ij}y_i + -0{,}25593_{PENF_i} + 0{,}06618_{PEF_i} + 20{,}0523_{PGR_i} + -7{,}56219_{PCW_i} + -4{,}88184_{LE_i} + -5{,}89744_{MYS_i} + \varepsilon_i$$

       Y_i :Constant Percentage of Poor Population in the i-th district/city
       $PENF_i$:Perkapita expenditure for non-Food in the i-th district/city
       PEF_i :Percentage of Perkapita Expenditure for Food in the i-th district/city
       PGR_i :Percentage of Population Growth Rate in the i-th district/city
       PCW_i :Percentage of Clean Water Households in the i-th district/city
       LE_i :Life Expectancy in the i-th district/city
       MYS_i :Mean Years of Schooling in the i-th district/city
       W_{ij} :Matric spatial balancer
       ε_i :Residuals from the i-th district /city

The effect of percentage of percapita expenditure for non Food (PENF)

The estimation result shows that the Percapita Expenditure non-food has a coefficient value of -0.25593 has a negative and significant effect with probability of Percapita Expenditure non-food is 0.00077. when there is an increase of 1 Rupiah variable will decrease the percentage of poor people amounted 0.25593 percent, if the value of Percapita Expenditure non-food in a district / city increases by 1 Rupiah and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can reduce the percentage of poor population by 0.25593 percent.

      Percapita expenditure to food is greater than to eat explained that people in a region there are already indications of welfare, engel's legal theory that the greater the proportion of non-food expenditure, the greater the welfare of the community. On the contrary, however, a smaller proportion of non-food expenditures reflects the declining welfare of its people. Indicators of improving people's well-being, assuming that once food needs are met, excess income will be used for non-food. Because the motive of consumption or consumption pattern of a community is determined by income. The results of the study (Massaid et al. 2019), Average per capita expenditure is the cost incurred for the consumption of all household members for a month divided by the number of household members. The higher the expenditure per capita, the higher the level of welfare of the population. In Indonesia, the amount of per capita non-food expenditure increases every year, followed by a decrease in the number of poor people. The results showed that for every one million rupiah increase in non-food expenditure per capita, the poverty percentage would decrease by 68.71%.

The effect of percentage of percapita expenditure for food (PEF)

The estimation result shows that the Percapita Expenditure For Food (PEF) has a coefficient value of 0.06618 has a positif and significant effect with probability of Percapita Expenditure For Food is 0.00013. when there is an increase of 1 Rupiah variable will increase the percentage of poor people amounted 0.06618 percent, if the value of Percapita Expenditure For Food in a district / city increases by 1 Rupiah and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can increase the percentage of poor population by 0.06618 percent.

      Percapita expenditure to food is how a population consumes from its income, in this section we can conclude that when the population is still focused on the expenditure to food then the population is assumed not to have obtained its welfare because the expenditure is still focused on basic needs, where this is the opposite side of engel's Theory of Law which states that the smaller the proportion of non-food expenditure, reflecting the declining level of welfare of its society. The Research conducted by (HASIBUAN 2020) examines how the consumption patterns of poor households by looking at expenditure per capita for food, an indicator of household welfare. The higher the household income, the smaller the proportion of expenditure on food to all household expenses. In other words, households tend to be more prosperous if the percentage of expenditure on food is much smaller than the percentage of expenditure on non-food. In Simalungun Regency, the average monthly expenditure for food is Rp 566,742, while the average monthly expenditure for non-food is Rp 314,052. So Simalungun Regency cannot be said to be prosperous, because the average expenditure is mostly used for consuming food.

The Effect of Population Growth Rate (PGR)
The estimation result shows that the population growth rate has a coefficient value of 20.0523 has a positif and significant effect with probability of population growth rate is 0.00000. when there is an increase of 1 thausand people variable will increase the percentage of poor people amounted 20.0523 percent, if the value of population growth rate in a district / city increases by 1 thausand people and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can increase the percentage of poor population by 0.06618 percent.

Population growth can have a negative or positive impact, the quantity of human resources needs to be balanced with adequate quality. In this case, quality is not only related to brain capacity, but also the physical capacity of human resources the high rate of population growth without sufficient human capital only increases the unemployment rate which ultimately increase the percentage of poverty. The results of the study by Irhamni (2018), finds that population have a positive and significant effect on poverty with the effect of increasing poverty by 6.25% in the long term. This happens because the increase in population is not accompanied by the progress of other development factors. Thus, growing population will actually lower wages and thus increase the burden on the economy.

The Effect of Percentage Of Poor Households Using Clean Water (PCW)
The estimation result shows that the household using clean water has a coefficient value of -7.56219 has a negative and significant effect with probability of household using clean water is 0.00160. when there is an increase of 1 percent variable will decrease the percentage of poor people amounted 7.56219 percent, if the value of household using clean water in a district / city increases by 1 percent and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can reduce the percentage of poor population by 7.56219 percent.

Water is one of the environmental components that is very important for development and growth for humans. Clean water plays a role in the scope of human capital development. In the regional dimension if the poor in a region have access and increased use of clean water can reduce the percentage of poverty, this refers to the welfare of living standards and the environment. This aspect also plays a role in improving good health for human capital. The results of the study by Qurratu'ain and Ratnasari (2016), find that predictor variables that have a significant negative effect on poverty levels are the school enrollment rate and the population with access to clean water. Meanwhile, for the results of grouping, the percentage of poor people in each district / city has an increasing trend every year so that there is a shift in the cluster that was originally located in a cluster with a high percentage of poor people to a cluster with a low percentage of poor people.

The Effect of Life Expectancy (LE)
The estimation result shows that the Life Expectancy has a coefficient value of -4.88184 has a negative and significant effect with probability of Life Expectancy is 0.00021. when there is an increase of 1 percent variable will decrease the percentage of poor people amounted 4.88184 percent, if the value of Life Expectancy in a district / city increases by 1 percent and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can reduce the percentage of poor population by 4.88184 percent.

The theory of poverty circles which states that public health is increasingly qualified is indicated by the increasing life expectancy. The increasing level of productivity of the community encourage the rate of economic growth that will ultimately reduce the poverty rate, meaning that the higher the life expectancy, the lower the poverty rate. Spatial dimension also shows how the life expectancy works where the increase in the quality of living standards of people in a region will be able to reduce the percentage of poverty. The results of the study by Niswati (2014), Health as measured by life expectancy has a negative effect on poverty in five districts/cities in Yogyakarta Province. This is because the life expectancy in Yogyakarta Province is high. Adequate facilities and infrastructure greatly support the quality of health in Yogyakarta Province.

The Effect of Mean Years of Schooling (MYS)
The estimation result shows that the Mean Years of Schooling has a coefficient value of -5.89744 has a negative and significant effect with probability of Mean Years of Schooling is 0.00004. when there is an increase of 1 percent variable will decrease the percentage of poor people amounted 5.89744 percent, if the value of Mean Years of Schooling in a district / city increases by 1 percent and independent variables, spatial weighting matrix (w) and residual (ε) is considered constant then it can reduce the percentage of poor population by 5.89744 percent.

Spatial analysis of services also shows how the increase in average length of school in a region will have an effect on the percentage of poverty reduction in each region. We can conclude that human capital has a central role in the problem of poverty and economic development, in addition to the presence of physical capital that has an effect on poverty and economic development. On the other hand human capital tends to have an accumulative and long-term effect compared to physical capital. The results of the study by Sakinah and Pudjianto (2018) Education has a negative significant impact on poverty in Gerbangkertosusila Area. That means, increasing education level to reduce poverty in this area is needed. It is important to increase educational attention such as ensuring the absence of dropouts for 12 years, optimizing the education budget, facilitating access to education in each regency/city, and increasing college scholarships.

CONCLUSIONS
The percentage of poor people among districts / cities in Lampung Province is known to have positive Moran's I values. This indicates that there is a spatial relationship in the form of positive autocorrelation, which means that the population between districts / cities in Lampung Province has a clustered pattern in 2015-2019. The Moran scatter plot shows a distribution pattern which is divided into 4 parts, namely the high-high, low-high, low-low and high-low areas, the LISA Cluster map describes the grouping of the percentage of poor people with an indication that the High-high area includes 3 areas. The LISA signification map at 0.05 significance has 2 regions, 0.01 has 1 significance area and 0.001 has 1 region. The SAR model is chosen to analyze cases of spatial linkages, has P-Value, AIC, R^2 and Log Likelihood that meet the requirements of using the model.

Percapita Expenditure For non-food has a significant negative effect on the percentage of poor people, Percapita expenditure for food has a significant positive effect on the percentage of poor people, The Rate of Population Growth has a significant positive effect on the percentage of poor people, Clean Water Households have a significant negative effect on the percentage of poor people, Life Expectancy has a significant negative effect on the percentage of poor people, Mean Years of Schooling has a significant negative effect on the percentage of poor people,.

The Provincial Government should put emphasis on hacking according to the characteristics of the poor in its district on poverty hacking of an area has a different character in population and indicators that cause a high percentage of poor people. Prevention of population displacement by not having human capital that expands to other regions certainly needs to be considered in order to emphasize the number of distribution to other regions, Policies that concern human capital is still very relevant and affects how the welfare of many people, the need for people's lives need to be put forward, the importance of making policies that fit the needs of the region and according to the characteristics of the population of the region must be stuttering in fact and circumstances, mistakes in the making will cause a widespread effect on poverty between regions.

Human capital is still the key to a prolonged economic development in its development it will have a widespread effect on poverty between regions. For the development of further research, it is suggested that the next researchers can add different human capital variables, as well as additional variables that cause poverty to increase in Lampung Province such as crime rates and dropout rates. The limitation of this research is the lack of macro and microeconomic variables in a narrow way, the next researchers are expected to consider and add the economic variables of each region.

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