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Modeling of Poverty Levels on the Island of Sumatra Using *Spatial Autoregressive*

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ABSTRACT: The purpose of this research is to determine the relationship between the poverty level in another province that is adjacent to the Sumatra island. The data was obtained from the Central Bureau of Statistics. The method used is Spatial Autoregressive (SAR). This model shows the relationship between areas that are close to each other and also describes how influential a causal factor variable is to the poverty rate. Based on the Moran Index, it is shown that adjacent provinces have similar poverty scores and Human Development Index (HDI) values. In the model, a significant variable was obtained: Mean Years of School (MYS) and Human Development.

KEYWORDS: Poverty Rate, Moran Index, Spatial Autoregressive

INTRODUCTION

Poverty is a global problem, often associated with difficulties and shortages to meet the needs of life. The high poverty rate will cause very bad impacts, such as increased crime, high mortality rates and many conflicts in society. Poverty is a social phenomenon experienced by a developing country, one of which is the Percent State of the Republic of Indonesia. In Indonesia, the central and regional governments are still trying to overcome the problem of poverty (Fajriawati, 2016). One of the regions of Indonesia with a high poverty rate is the island of Sumatra.

The island of Sumatra, which consists of 10 provinces, has a different percentage of poverty levels in each province. Based on poverty data that Retrieved from Body According to the Center for Statistics (BPS) in 2019, it is known that the percentage of national poverty is 9.22% (bps.go.id, 2021). The island of Sumatra has several provinces with a higher percentage of poverty than the national poverty percentage. Four out of 10 provinces on the island of Sumatra have a percentage of poverty levels above the percentage of the national poverty rate in 2019. Different poverty levels in a region are very likely to be influenced by the environment around that area. Based on this description, in the case of poverty, it is suspected that there is a relationship between regions (unit of analysis), so to analyze it, it is necessary to pay attention to the elements of spatial data.

In spatial data, observations in an area depend on observations of adjacent areas. This is in accordance with Tobler's law which reads "everything is related from everything else, but near things are more related than distand thing". Everything is interconnected with each other, but something close is more influential than something far away. Spatial effects occur between one area and another. In analyzing spatial data, the spatial regression method is used. Spatial regression is the result of the development of classical linear regression. The basis of the development of spatial regression is because Presence influence place or spatial on the data analysis (Novitasari & Khikmah, 2019a). In this case, the poverty rate is not only influenced by independent variables but there are spatial effects in it.

Research that discusses poverty by (Putri et al., 2018) Obtaining the results of all independent variables, namely health service facilities, number of school facilities, number of population density, number of people with social welfare, and significant village distance to poverty level. Furthermore, the research conducted by (Ratifah et al., 2019) resulting in school participation rates (APS) aged 16-18 years and population aged 10 years and above with the highest education completed by junior high school are factors that affect poverty in every district/city in East Java. Furthermore, the research conducted by (Rahmadeni, 2020) with the results of research on the variables of HDI, Education, GDP and unemployment have a strong influence on the poverty rate using the SEM model.

Based on previous research by (Putri et al., 2018)(Ratifah et al., 2019) and (Rahmadeni, 2020), some of the factors that affect poverty are Gross Regional Domestic Product (GDP), average length of schooling, unemployment and the Human Development Index (HDI). So that the author is motivated to look at the factors that affect the poverty level on the island of Sumatra with a data spatial regression approach. For this reason, the author is interested in taking the title "Modeling the

Poverty Level on the Island of Sumatra Using *Spatial Autoregressive*"

METHOD

This study uses a quantitative method. The research began by collecting secondary data with data obtained from the Central Statistics Agency, namely poverty data, Gross Regional Domestic Product (GDP), Education Level, Unemployment, and Human Development Index (HDI) in 2019. The data used is data from each province on the island of Sumatra, namely Aceh, North Sumatra, West Sumatra, South Sumatra, Riau, Riau Islands, Bangka Belitung, Jambi, Bengkulu and Lampung. This study uses the *Spatial Autoregressive* method in determining variables that affect the poverty level.

1. *Spatial Autoregressive* (SAR)

Spatial Autoregressive is a linear regression model in which there is a spatial relationship to the dependent variable. This model is commonly given the mixed name autoregression because regression combines ordinary regression with a lag spatial regression model on dependent variables. Equation (1) is the model *Spatial Autoregressive* (Mariana, 2013).

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2\mathbf{I}) \qquad (1)$$

Information:

$\mathbf{y}$ = vector of dependent variables with size $n\,x1$,

ρ = the spatial coefficient of lag of the independent variable of the size $|\rho| < 1$,

$\mathbf{X}$ =kmatrixkindependent variable of size $nx(k+1)$,

β = parameter vectorspatial coefficients of the size error , $k\ x\ 1$

ε = vector-sized *error* $n\,x1$

2. Moran Index

The moran index is used to see the identification of a location in spatial grouping or spatial autocorrelation. Spatial autocorrelation is the correlation between a variable and itself based on space. The statistical test of the morans index for an observation vector $Y_n = (Y_{n1}, \ldots, Y_{nn})$ at n locations. The Morans Index *I* formula for standardized spatial weighting (W) matrix is:

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

Information:

I = moran index

n = Number of occurrence locations

x_i = value at location *i*

x_i = value at location to j

$\bar{x}$ = average number of variables

w_{ij} = elements on the standardised weighter between *i* and *j*

The expected value of the Moran Index, is formulated in equation (3):

$$I_0 = E(I) = \frac{-1}{n-1} \qquad (3)$$

The Moran *Scatterplott* Index is a diagram to see the relationship between the observed mileage at a location (standardized) and the average observation value of the locations adjacent to the location in question.

If *I* > *I0*, then the autocorrelation value is positive (Group data pattern)

If *I* = *I0* means that there is no spatial autocorrelation

If *I* < *I0* means that the autocorrelation value is negative, this means that the data pattern is spreading.

The division of the quadrants is as follows:

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

Quadrant I is called *High-high* shows a high observation value surrounded by an area that has a high observation value opposite to the third quadrant called *Low-Low*, showing low observation values surrounded by areas with low observation values. Quadrant II is called *Low-High*, shows a low observation value surrounded by an area that has a high observation value opposite to quadratic IV called *High-Low*, showing high observation values by areas with low observation values (Hernawati & Ardiansyah, 2018).

3. Spatial Inverter Matrix

To determine the relationship between one region and another, a spatial weighting matrix is used. The relationship of proximity can be known through 2 sources, namely proximity (area) and distance (point). The spatial weighting matrix is notated , and with its elements . The general forms of spatial matrices are as follows $\boldsymbol{W}\boldsymbol{W}_{ij}(\boldsymbol{W})$(Lokang & Dwiatmoko, 2019) :

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{n2} \\ \vdots & \vdots & \cdots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix}$$

The elements of the *Contiguity matrix* W_{ij} are defined through the equation:

$$W_{ij} = \begin{cases} 0, \; jika \;\; i \; dan \; j \; tidak \; bertetagga \\ 1, \; jika \; i \; dan \; j \; bertetagga \end{cases}$$

In this study, the *Queen Contiguity* matrix was used. This method allows researchers to see the neighborhoods of each province based on the intersection of sides and angles. So that every province that borders directly is a neighbor. Figure 1 is an illustration of *contiguity weights*

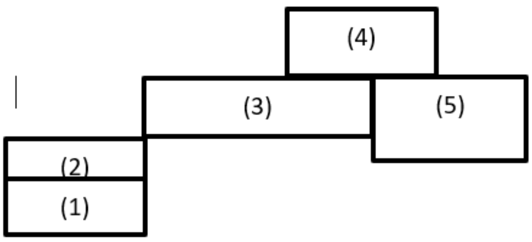

Figure 1. Illustration of Spatial Weighting

Based on figure 1 The weighting matrix using *Queen Contiguity* is as next:

$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

The following is a standardized spatial weighting matrix from Figure 4 (Djuraidah & Wigena, 2012) :

$$\mathbf{W}_{queen} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix}$$

RESULTS AND DISCUSSION

The distribution of poverty levels on the island of Sumatra varies from province to province. In this study based on the number (in percent), the poverty level is grouped or mapped into 3 regions, the mapping can be seen in Figure 2:

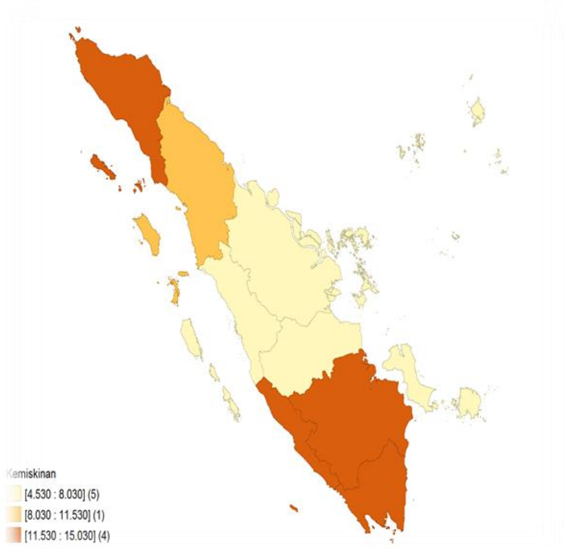

Figure 2. Poverty Rate Distribution Map

Based on Figure 5, it can be seen that white indicates the lowest poverty level and so on until the dark brown color indicates the highest number of poverty levels, from the map of the distribution of poverty levels on the island of Sumatra, for example in Aceh Province the color is dark brown and the province of North Sumatra is brown and it can be stated that the province of Aceh has a higher poverty rate than the province of Sumatra North, when viewed from the geographical location that these two provinces have close distances, so that North Sumatra Province will have the potential to have the same level of poverty.

1. Spatial Inverter Matrix

In spatial analysis to determine the presence of spatial autocorrelation, the main component required is a location map. The map is used to determine the close relationship between provinces on the island of Sumatra. Thus it will be easier to give weights to each location or province. From the map of the island of Sumatra, it is known that there are 10 provinces so that the spatial weighting matrix is . 10×10 The method used in creating the matrix is the *Queen Contiguity method*.

2. Testing Spatial Effects Using Moran Index

The Moran index is used to determine the autocorrelation of an observation to the same observation in another adjacent area. The value of the Moran Index is determined using the formula in Equation 2. The Moran Index values for each variable are seen in Table 1

Table 1. Moran Index

Variable	Moran Index Value
y	0.249
x_1	-0.097
x_2	-0.130

x_3	-0.138
x_4	0.092

Table 1 shows that the Moran Index value of the poverty level variable (*y*) and the Human Development Index (x_4) have a positive value, namely I > 0 which shows a positive autocorrelation, i.e. the data shows similarity in values from adjacent locations and tends to be grouped. Meanwhile, the variables of Gross Regional Domestic Product (x_1), Average School Length (x_2) and Open Unemployment Rate (x_3) have a negative autocorrelation, which shows that adjacent locations have different values and tend to spread. The *Scatterplots* for each variable are as follows:

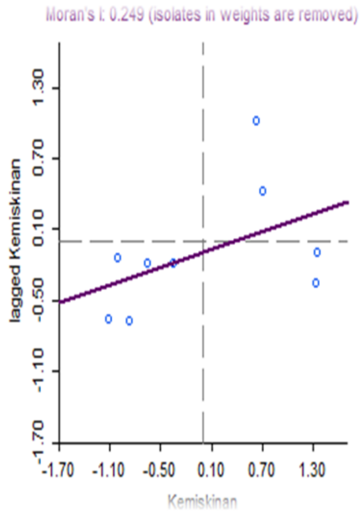

Figure 6. Poverty Level Spread Scatterplot

Based on Figure 6, it shows that the distribution of poverty variables is grouped in quadrant III *(Low-low)*, meaning that provinces on the island of Sumatra with low poverty levels tend to be close to provinces that have low poverty levels. However, there are also several provinces in quadrants I and IV which indicates that there are several provinces with high poverty levels that tend to be close to provinces that have high poverty levels as well and provinces with high poverty levels tend to be close to provinces with low poverty levels.

3. Parameter Estimation

Parameter estimates in the SAR model are presented in Table 2 below:

Table 2. SAR Parameter Estimation

Variable	Coefficient	Std.Error	z-value	Prob
W_y	0.707	0.153	4.604	0.000
CONST	101.56	36.57	2.777	0.005
GDP	-0.226	0.647	-0.349	0.726
RLS	-4.015	1.383	-2.903	0.003
TPT	0.760	0.570	1.332	0.182
IPM	-0.907	0.462	-1.959	0.050

Based on Table 1, several variables have $|Z_{hitun}| > Z_{0,05}$ a value or probability value of $>\alpha$, namely the average length of schooling (x_2) and the Human Development Index (x_4) have a negative influence on the poverty rate, while the variables that do not have a significant effect are the Gross Regional Domestic Product (GDP) and the Open Unemployment Rate (TPT). From Table 2, the *Spatial Autoressive* (SAR) equation is formed:

$$\hat{y}_i = 101,568 + 0,707378\sum_{j=1,i\neq j}^{10} W_{ij}y_j - 0,22644x_1 - 4,01547x_2 + 0,760856x_3 - 0,907122x_4$$

In general, the *Spatial Autoregressive model* can be interpreted, that if other factors are considered constant, and if the gross regional domestic product (x_1) increases by one percent then reduces the poverty rate by 0.226449, the average length of schooling (x_2) increases by one percent will reduce the poverty rate by 4.01547, unemployment (x_3) increases by one percent will increase the poverty rate by 0.760656 and if the human development index (x_4) increase by one percent, it will reduce the poverty rate by 0.907122. The coefficient of w_y = 0.707378 the influence of each surrounding area can be measured as 0.707378 times the average response variable around it.

CONCLUSIONS

The Autoregressive Spatial Model obtained shows that there is a relationship between the poverty level in one province and the poverty level in other adjacent provinces, namely by looking at the value of the moran index at the poverty level of 0.249, where the value is greater than the expected value of the moran index value, meaning that the data shows the similarity of values from adjacent locations and tends to be grouped. This causes the high poverty rate to also be influenced by the poverty level in other provinces adjacent to other provinces.

Furthermore, based on the *Spatial Autoregressive* (SAR) model, it is estimated that the factors that affect the poverty rate on the island of Sumatra are the Average School Length and the Human Development Index. And for readers who are interested in continuing this research, they can add influential variables or can use other weights so that they can be seen more in areas where the poverty level factor is more influential.

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