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Poverty Analysis In Riau Province : Spatial Econometric Approach

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ABSTRACT

Poverty is indeed a major problem in a country, many various poverty factors occur. This study was conducted to see the influence of the relationship between poverty areas and other poverty areas, with an econometric spatial approach. It is hoped that the approach model can analyze the factors that affect the category of poor people in Riau Province. Data analysis using Spatial Regression with the help of Geoda software to perform spatial tests. with the data used is the Number of Poor People as the dependent variable, while the independent variables are GDP ADHK, District Minimum Wage, Human Development Index. The results of this study show that spatially poverty, minimum wage, HDI, and GRDP have a positive spatial relationship. Meanwhile, according to LISA (Local Indicator of Spatial Autocorrelation) as a whole, significant clusters in each variable vary in each region. However, the relationship between GRDP, HDI, and MSEs is not significant for poverty.

***Keywords**: Poverty, Spatial Econometrics*

INTRODUCTION

The Indonesian Central Bureau of Statistics (BPS) released the number of poor people in Riau Province in 2022, recorded at 485.03 thousand poor people in Riau. Of the 12 districts / cities, the highest poor population is in Rokan Hulu Regency, with a total poor population of 73.81 thousand people. The Chamber and Nasikun divide poverty into four inner sections: (Adawiyah, 2020). They are absolute poverty, relative poverty, cultural poverty, and structural poverty. Where the four divisions of poverty explain the factors that cause poverty. Which includes family needs, government policy factors, and environmental factors and one's nature. According to the Chamber in (Girsang, 2015) Mentions five elements *of the vicious cycle of poverty* : material poverty, physical weakness, isolation, and insecurity and helplessness. Where each category of poverty circle has factors from the emergence of poor people, namely factors of insufficient needs, factors of education, and factors of investment (savings).

Based on data released by BPS Riau Province in 2022, it was recorded that as many as 12 districts with the highest percentage of poverty were in the Meranti Islands region at 23.84%, Rokan Hulu Regency at 9.95%, and Pelalawan Regency at 8.97%. The three districts reflect that the poor population in Riau Province is still in areas far from the downtown area of Riau Province. Thus, poverty in rural areas causes population migration to cities and growth centers to be inefficient and weak in providing services to the community. Thus the village becomes underdeveloped and undeveloped (Hasibuan et al., 2019). In this case, the Riau Provincial Government provides a formulation for solving the poverty problem, so that the poverty rate in Riau Province does not increase, especially in the Meranti Islands, Rokan Hulu, and Pelalawan Regencies. From these problems, it can be concluded that the purpose of this study is to see the influence of the relationship between poverty areas and other poverty areas, with an econometric spatial approach. It is hoped that the approach model can analyze the factors that affect the category of poor people in Riau Province. And the results of this study can be used as a reference in alleviating poverty.

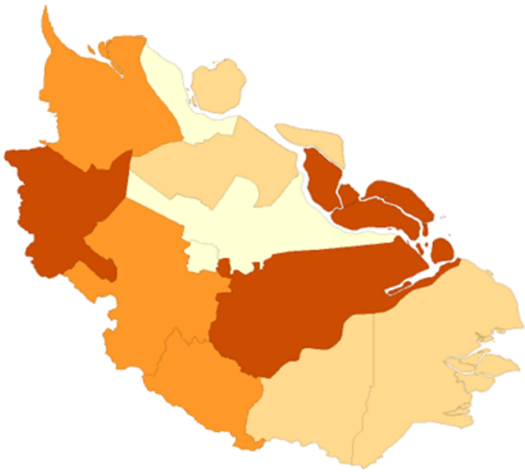


Figure 1. Spread of the Poor Residents of Riau Province 2022

This study uses Growth Effect Theory, and Inequality Effect Theory taken from the research of Deininger and Squire, Ravallion, 2001, Dollar and Kraay, 2000, Kuznet, 1995, Lewis, 1954, Fields, 1980 in (Puspitasari et al., 2012a). And Solow Swan's Growth Theory, as well as Micro-Oriented Economic Growth Theory (Bagliano & Bertola, 2004) deep (Sameti & Farahmand, 2009a). Growth Effect Theory says that inequality comes from economic growth and then poverty, while Inequality Effect Theory says that Economic Growth will lead to inequality, resulting in poverty. Meanwhile, according to Solow, Swan assumes that the economy is at the level of full *employment and* the level of full utilization *of* production factors. In other words, the economy will continue to grow and everything depends on population growth, capital accumulation, and technological progress and Micro-Oriented Economic Growth Theory, namely income inequality affects micro-oriented economic growth, heterogeneous consumer behavior and inseparability of investment with aggregate demand.

If you look at research from (Sameti & Farahmand, 2009) using spatial regression with the aim of analyzing the spatial relationship between poverty, income inequality and economic growth in Euro-Mediterranean countries. With the results found that the relationship between economic growth and poverty is bilateral, while the relationship between poverty growth and inequality poverty is one-way. While some studies look at spatial effects, such as using Spatial Autoregressive Models, Spatial SUR, Moran's I Test and LISA *(Local Indicator of Spatial Autocorrelation),* Spatial Autocorrelation, Spatial Panel Data and SAR Fixed Effect (Aminuddin Anwar, 2022; Delgado Narro, 2020; Liu et al., 2023; Peirovedin et al., 2016; Pramono & Marsisno, 2018; Pratama et al., 2021; Puspitasari et al., 2012b, 2022; Wibowo et al., 2023; Zhang et al., 2023) This model shows the results of spatial relations of the area studied. With the various advantages of each spatial modeling.

This study aims to explore and analyze the poverty rate in Riau Province using an econometric spatial approach. The main objective of the study is to identify spatial patterns of poverty in the region, understand the factors that contribute to economic inequality, and devise policy recommendations that can help reduce poverty levels effectively. By combining econometric analysis and spatial elements, this study is expected to provide a deeper understanding of the geographical distribution of poverty and the environmental factors that influence it. The benefits of this research are very significant in the context of economic development and community welfare in Riau Province. With a better understanding of the spatial patterns of poverty, governments and policymakers can design more targeted and efficient intervention strategies. In addition, the results of this study can make a positive contribution in the development of sustainable economic policy models, focusing on reducing regional inequality. Thus, this research is expected to provide a more holistic and sustainable view of the problem of poverty in Riau Province, as well as support efforts to improve the quality of life of local communities.

METHOD

This research data comes from BPS Riau with a research period of 2020-2022. Data analysis using Spatial Regression with the help of Geoda software to perform spatial tests. The research area consists of 12 regencies/cities in Riau Province. The variable used is poverty with reference to data, namely the number of poor people who act as a dependent variable. and the independent variable is the human development index (HDI) using reference data, namely the HDI method of Riau Province, district minimum wage (UMK) and gross regional domestic product (GRDP) reference data, namely GRDP on a constant price basis.

Spatial Econometrics

It is an inference estimation technique to determine the quality relationship between one variable and another variable after taking into account territorial/spatial aspects. The spatial aspect of a variable alone can actually be known using the Moran index estimation technique which is mathematically presented in the following equation (Pohan, 2019) :

$$I\left[\frac{n}{\sum_{i,j}\boldsymbol{W}_{i,j}}\right]\frac{\sum_{i,j}\boldsymbol{W}_{i,j}(X_i-\chi)\,(x_j-\chi)}{\sum_i(x_i-\chi)^2}$$
(1)

Where $x=\left[\frac{1}{n}\right]\sum_i X_i$ dan $\boldsymbol{W}_{i,j}$ is a weight matrix of size n x n (n is the number of areas under consideration because it is considered neighborly) so that the weight matrix will always be a square matrix. For a hypothetical intensity region as illustrated in figure 1.c below, the weight matrix would be 55.×

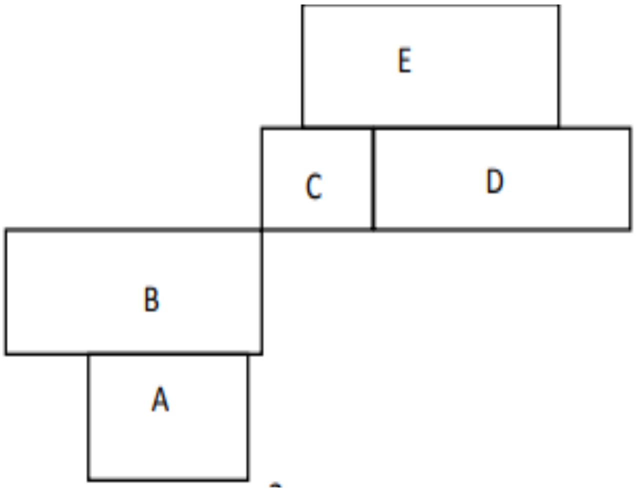


Figure 2. Econometric Spatial Relations

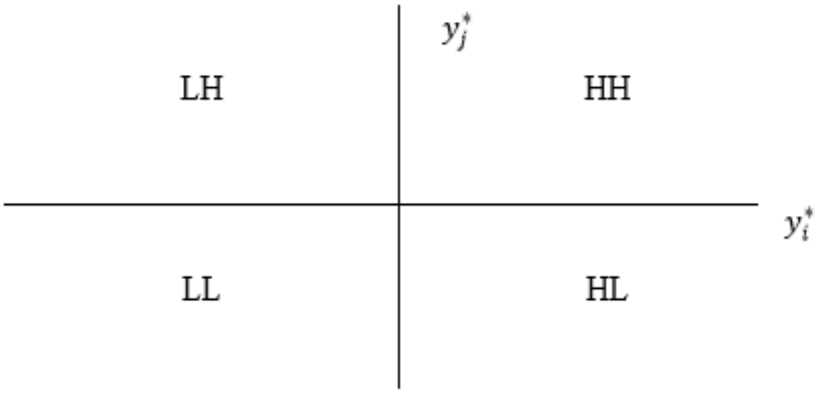
Spatial Weighting Matrix

The spatial weighting / weighing matrix or denoted by ($\boldsymbol{W}$) can be obtained based on distance information from neighborhoods, or in other words from the distance between one area and another. There are several methods for defining *contiguity* between regions according to (Dolores Ugarte, 2011) among others: *Linear contiguity* , *Double linear contiguity* , *Bhisop contguity* , *Rook contiguity* , *Queen contiguity* , *Double Rook contiguity* .

Spatial Autocorrelation Method

In the literature, this new convergence analysis $\beta$is carried out taking into account spatial effects. In addition, empirical studies that measure regional convergence from an econometric spatial perspective have shown that spatial extenality and spillovers are essential in the analysis of growth patterns and provide richer insights for regional economic growth and convergence processes (Rey & Montouri, 1999). Thus, spatial autocorrelation should be considered in regional analysis. Spatial autocorrelation is defined as the correlation between these values in geographic space, which causes deviations from the assumptions of independent observations of classical statistics (Griffith & Chun, 2014). The most common measure of spatial dependence is moran'I, as it provides a strong measurement and is sensitive to extreme values. There are two kinds of spatial autocorrelation models, namely *global moran's I and local moran's I* known as local indicator of spatial association (LISA) (Anselin, 1995).

Local moran's I can also be presented in the form of the moran's scatter plot. This study adopted the concept of moran scatteer plot from Anselin (1995). The moran scatter plot is divided into four quadrants: (1) the high-high (2) the high-low (3) the low-high (4) the low-low. Quadrant positioning based on variable values in the observed area and variable values in neighboring areas, where and dam this figure shows the moran's scatter plot.$y_i y_j y_j \ = \ y_i - y y_j \ = \ \sum_{j=1}^{n} w_{ij} y_j \, y_j = y_j - y$



Gambar 3. The moran's I scatter plot

Quadrant (1) HH indicates that areas with high y values appear to be surrounded by other areas with high y-values anyway. Quadrant (2) HL indicates the area with a high y value visible around other areas with low y values. Quadrant (3) LH indicates that the area with a low y value appears to be surrounded by another area with a high y-value. Next, quadrant (4) LL indicates that the area with the low y value appears to be surrounded by other areas with a low y-value anyway.

RESULTS AND DISCUSSION

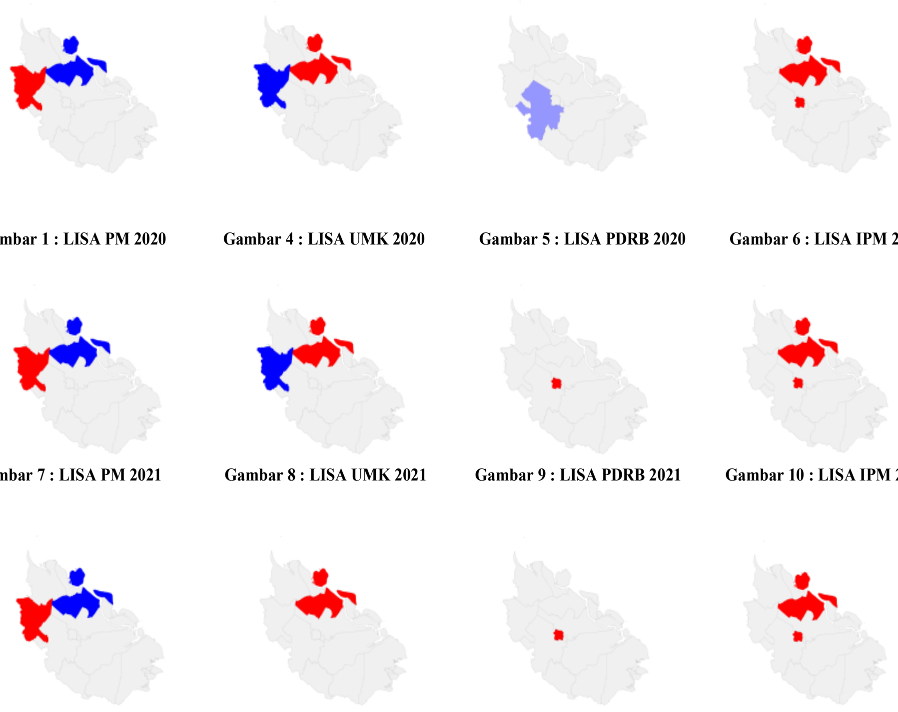
Autokorelasi Spasial (Moran's I & Lisa (Local Indicator Of Spasial Autocorrelation))

To determine whether there is a spatial relationship between neighboring variables in an area, a spatial dependency test is carried out, by looking at the value of Morans'I in table 3. If you look at the value of Morans'I in the research year, namely 2021 and 2022, all variables studied have positive spatial autocorrelation, which means that adjacent locations have a positive value-added influence (variables studied) between districts / cities with one another, have values that tend to be similar and grouped. Meanwhile, in 2020, in the GRDP variable, Morans'I value is negative. This means that the GRDP variable has a negative spatial autocorrelation value, which means that the GRDP variable has a value that tends to spread out.

Table 1. Morans'I Value Per Year (Geoda Software)

Year	Variables	Morans'I
2020	PM	0.242 (+)
	UMK	0.238 (+)
	PDRB	0.213 (-)
	IPM	0.204 (+)
2021	PM	0.256 (+)
	UMK	0.238 (+)
	PDRB	0.111 (+)
	IPM	0.194 (+)
2022	PM	0.283 (+)
	UMK	0.256 (+)
	PDRB	0.126 (+)
	IPM	0.227 (+)

Furthermore, to find out areas that have locally significant spatial autocorrelation can use the Local Indicator of Spatial Autocorrelation (LISA). If you look at the output of LISA results processed through Geoda in 2020, overall, significant clusters in each variable vary in each region. For the variable of poor people, the highest significant cluster is in Rokan Hulu Regency. Because the Rokan Hulu region has the highest number of poor people and neighboring Rokan Hulu Regency has a high number of poor people. Or Rokan Hulu Regency is in the High to High quadrant. While the lowest significant cluster is in the Bengkalis Regency area. Because the number of poor people in Bengkalis Regency is high, but neighboring Bengkalis Regency has the lowest number of poor people. Or Bengkalis Regency is in the High to Low Quadrant. For the Minimum Wage variable, it shows the same area as the result of the 2020 poor population LISA variable, if you look at the GRDP variable, the Kampar Regency area shows the lowest to highest significant cluster (Low to High), meaning that the GRDP in Kampar Regency has the smallest value of Rp.514,193, while in neighboring areas, namely Pekanbaru City and Rokan Hulu Regency has the highest GDP value of Rp.6,900,014,- and Rp.296,085,502,-. Meanwhile, the HDI 2020 variable, the area that shows the highest significant cluster is in Bengkalis Regency (High to High). This means that the Human Development Index in Bengkalis Regency has the highest value, as well as neighboring neighbors opposite Bengkalis Regency, namely Dumai City, Pekanbaru City, and Siak Regency. If you pay attention to the color patterns tend to be dark (the case of the variable as a whole) it means that the region contributes significantly to the results of global spatial autocorrelation positively.



Gambar 1 : LISA PM 2020 | Gambar 4 : LISA UMK 2020 | Gambar 5 : LISA PDRB 2020 | Gambar 6 : LISA IPM 2020

Gambar 7 : LISA PM 2021 | Gambar 8 : LISA UMK 2021 | Gambar 9 : LISA PDRB 2021 | Gambar 10 : LISA IPM 2021

Gambar 11 : LISA PM 2022 | Gambar 12 : LISA UMK 2022 | Gambar 13 : LISA PDRB 2022 | Gambar 14 : LISA IPM 2022

Figure 4. Annual Per-Variable LISA Cluster Map (Geoda Software)

For the 2021 LISA analysis, it was not much different in 2020 for the variables Poor Population, Minimum Wage, and HDI. However, for the Pekanbaru City area is in the highest significant cluster (High to High). Namely that the GRDP in Pekanbaru City has the highest GRDP value along with the neighbors opposite Pekanbaru City, namely Bengkalis Regency, Kampar Regency, Pelalawan Regency, and Siak Regency. For 2022, the variables of Poor Population, GRDP, and HDI are almost the same as the output of the analysis in 2021. Especially the Bengkalis Regency area, the variable Minimum Wage is in the highest significant cluster (High to High).

Spatial Regression Modeling

To find out the best spatial modeling results, modeling analysis was carried out at Geoda. For spatial modeling analysis, it is carried out by checking the results of spatial regression in the nature of OLS (ordinariy least square). After that, pay attention to the probability value of the spatial model you want to analyze. In the results of the spatial report, we can see the models that need to be analyzed, such as SAR (Spatial Autoregressive Model), SEM (Spatial Error Model) and OLS (Ordinary Least Square) models. To see which model is the best of the three models, it is necessary to pay attention to the output results of the Geoda software.

From the results of spatial statistical output, no modeling can be used. Both SAR modeling and SEM modeling. Because the probability value shown in the table is above the significance limit of α 0.05. hence the best modeling is OLS Spatial modeling.

Table 2. Determination of the Best Model (Geoda Software)

YEAR	TEST	VALUE	PROB
2020	SAR	1.0112	0.31461
	SEM	0.0154	0.90135
2021	SAR	2.4468	0.11777
	SEM	2.0740	0.14983
2022	SAR	2.8329	0.09235
	SEM	1.7917	0.18072

Table 3. Spatial Regression Per Year (Geoda Software)

Y (PM)	2020			2021			2022		
	Coefficient	**t-stat**	**Prob**	**Coefficient**	**t-stat**	**Prob**	**Coefficient**	**t-stat**	**Prob**
C	300.003	3.076	0.015	355.516	2.846	0.021	332.249	2.764	0.024
UMK	-6.6239	-2.161	0.062	-7.4950	-1.971	0.084	-7.7822	-2.229	0.056
PDRB	1.1404	1.902	0.093	0.00019	0.593	0.569	0.00020	0.683	0.513
IPM	-0.9007	-0.903	0.392	-1.3066	-0.824	0.433	-0.8192	-0.507	0.625
F_{hitung}	**4.157**			**2.201**			**2.367**		
P-Value	**0.047**			**0.165**			**0.146**		
R^2	**0.6092**			**0.4522**			**0.4702**		
AIC	**98.7028**			**103.701**			**102.046**		

If you look at the results of the classic spatial regression in table 3, it shows that the variables studied, namely Minimum Wage, Gross Regional Domestic Product, and Human Development Index from 2020 to 2022 in the T test, show that there are no significant variables studied for poor people in Riau Province. Which is characterized by a probability value greater than the significance limit of 0.05. Meanwhile, the results of statistical tests, namely Probability F-Statistics,α show that only in 2020 all independent variables have a relationship with the number of poverty population (dependent variables) in Riau Province. Meanwhile, in 2021 and 2022 there is no simultaneous influence on the dependent variable. And for the value of the Coefficient of Determination (R2) shows that in 2020 the value of R2 is 0.6092. which means that 60.92% of the variables of Minimum Wage, Gross Regional Domestic Product, and Human Development Index affect the poor population in Riau Province. Meanwhile, in 2021 and 2022 only got R2 values of 45% and 47% The values entered into the spatial regression equation are as follows:

$$Y_{2020} = 300.003 - 6.6239_{X1} + 1.1404_{X2} - 0.9007_{x3}$$
$$Y_{2021} = 355.516 - 7.4950_{X1} + 0.00019_{X2} - 1.3066_{x3}$$
$$Y_{2022} = 332.249 - 7.7822_{X1} + 0.00020_{X2} - 0.8192_{x3}$$

To see if this study has met the classical assumption test, namely the Normality Test and the Heteroscedasticity Test. So table 4 shows that all classical assumption tests have been fulfilled, both from 2020 to 2022. With reference to normality values above the significance limit of α 0.05. If the normality value is above 0.05 then the data is normally distributed. While the reference value of heteroscedasticity using the value of the Breusch-Pagan test. If the Breusch-Pagan test value is above the significance limit of 0.05, then there is no heteroscedasticity.$\alpha\alpha$

Table 4. Classical Assumption Test Per Year (Geoda Software)

Year	Normalitas	Heteroskedastisitas
2020	0.60592	0.58926
2021	0.64872	0.72352
2022	0.51776	0.87204

CONCLUSION

From the results of the spatial autocorrelation analysis, it shows that poverty, district minimum wage, gross regional domestic product, and human development index have positive spatial relationships, unless the GDP variable in 2020 shows negative values. Spatial Local Indicator Of Spatial Corrrelation (LISA) shows significant clusters in each variable vary in each region per variable studied. And the spatial modeling chosen is OLS (Ordinary Least Square). With reference to the modeling probability value, if the intended model has a signification value of α above 0.05 for all models, then the model chosen is OLS. Statistically, there is no relationship between poverty variables that occur in Riau Province, with proof of probability values above the significance of α 0.05. In this study, of course, it has strengths and limitations in analyzing poverty that occurs in Riau Province. To reduce poverty, the government needs to make policies or regulations in alleviating poverty, especially in Rokan Hulu Regency with the highest number of poor people. For future researchers, they can use Spatial Econometrics analysis by using panel data and adding variables that are still related to poverty.

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