Spatial Inequality of Poverty In Lampung Province In The Perspective of Sustainable Development Using Autoregressive Spatial Approach and Spatial Error Model

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Abstract.
Spatial regression is a development of classical regression that considers the influence of location between regions. This study aims to determine the factors that influence poverty in Lampung Province in 2024, determine the best model through a comparison of the Spatial Autoregressive (SAR) and Spatial Error Model (SEM) methods, and identify spatial patterns of poverty in Lampung Province. Model parameter estimation is carried out at each observation location using a spatial weighting matrix of Rook contiguity to capture the proximity between regions. Based on the Lagrange Multiplier test, the SAR model is identified as the best model, because it is able to capture the influence of interregional linkages through significant spatial coefficients with an AIC value of 136.3521. The SAR parameter estimation results show that the population (X_3) with a p-value of <2.2e-16 and the human development index (X_4) with a p-value of 0.006990, with a significance level or α <0.10, have a significant effect on the number of poor people in Lampung Province, while gross regional domestic product (X_1) and TPAK (X_2) have no significant effect. The Local Indicators of Spatial Association (LISA) analysis also revealed the existence of High-High and Low-Low poverty clusters indicating spatial grouping in several regencies/cities in Lampung Province. However, after SAR modeling, the residual map of the SAR model shows a scattered spatial pattern and does not form a geographic cluster, indicating that the influence between regions has been successfully captured by the model. This finding confirms that poverty in Lampung Province is not only influenced by the internal characteristics of the region, but is also influenced by the conditions of the surrounding areas. Therefore, policy actions need to consider the spatial effects between regions so that poverty alleviation programs are more targeted and effective.
Keywords: *Poverty, OLS, SAR, rook contiguity*

I. INTRODUCTION

Poverty is still the main problem faced by various countries, including Indonesia. This issue not only reflects economic disparities, but also illustrates complex development challenges. Poverty cannot be explained only from one side, but needs to be understood in a multidimensional way because it includes aspects of people's lives. According to (Fauziah et al., 2021), poverty cannot be explained only from lack of income. This view shows that poverty has interrelated social, economic, and structural dimensions. Until now, poverty is still a central issue faced by developing countries, including Indonesia (Amirah et al., 2024). In addition to affecting the economic aspect, poverty also has a wide impact on access to education, health, and community welfare. Therefore, poverty alleviation is one of the main pillars in the Sustainable Development Goals (SDGs) agenda.

Nationally, Indonesia has experienced a decrease in poverty rates in recent decades (Agus Triono & Sangaji, 2023). This poverty alleviation effort shows the government's commitment to improving people's welfare. As part of the global community, Indonesia also plays an active role in supporting the sustainable development agenda contained in the 2020-2024 National Medium-Term Development Plan (RPJMN) (Gabriela & Utomo, 2023).

Although the poverty trend shows a decrease, the number of poor people in Indonesia is still relatively high. Based on data from the Central Statistics Agency (BPS), the number of poor people in Indonesia in March 2023 was 25.90 million people, down from 26.36 million people in March 2022. This means that poverty reduction has indeed occurred, but it still leaves a gap between regions. These differences reflect the existence of inequality between regions, both in terms of economy and social welfare, which is still relatively high (Ningrum et al., 2024). One form of inequality between regions that emerges is spatial inequality of poverty, which is the difference in poverty levels between regions that are geographically interrelated.

In Lampung Province, this inequality is an important problem because areas in Lampung Province have diverse socio-economic characteristics between districts/cities. Based on data from the Central Statistics Agency of Lampung Province, the poverty rate in Lampung Province in March 2023 was 11.11%. Several districts in Lampung Province that still have a high poverty rate include East Lampung at 13.80%, West Coast at 13.49%, Pesawaran at 12.89%, and South Lampung at 12.79%. In general, this condition indicates a striking difference in the level of community welfare between regions in Lampung Province.

The fact that the difference in poverty rates between regions shows that there is a spatial imbalance in poverty in Lampung Province that has not been fully identified and analyzed in depth. The inequality not only illustrates the difference in numbers, but also reflects an imbalance in access to development resources, infrastructure, and public services. Therefore, understanding the spatial dimension of poverty is very important so that poverty alleviation policies are more targeted, region-based, and sustainable.

Poverty data can be analyzed using multiple linear regression (OLS). Multiple linear regression is a basic model for looking at the relationship between bound variables and independent variables. Through this analysis, it is possible to identify the factors that have a significant effect on the poverty level before a more complex spatial analysis is carried out.

Spatial data found in the field cannot be modeled with multiple linear regression (OLS), so it requires Spatial Autoregressive (SAR) and Spatial Error Model (SEM) models. Spatial Autoregressive (SAR) and Spatial Error Model (SEM) are two quantitative approaches that can be used to analyze patterns of inequality and spatial linkages between regions. This approach takes into account spatial weights based on the distance between regions and geographic coordinates (latitude & longitude). The selection of the right weights is essential in Spatial Autoregressive (SAR) and Spatial Error Model (SEM) analysis. This model was applied to poverty data in this study.

Based on the presentation that has been delivered, the researcher is interested in conducting a research entitled "Spatial Inequality of Poverty in Lampung Province in the Perspective of Sustainable Development Using Spatial Autoregressive Approach and Spatial Error Model".

II. METHODS

Experimental (or Materials and Methods)

This research was carried out in the even semester of the 2024–2025 Academic Year at the Faculty of Science and Technology, Nahdlatul Ulama University Lampung by utilizing secondary data on the number of poor people in Lampung Province in 2024 obtained from the Central Statistics Agency (BPS) of Lampung Province. The research used supporting devices in the form of laptops, RStudio version 4.2.3 for data processing, Mendeley Desktop for reference management, and stationery and other administrative equipment. The variables analyzed consisted of the number of poor people as a dependent variable (Y), while independent variables included economic growth (GDP), labor force participation rate (TPAK), population number, and Human Development Index (HDI). The research stage begins with data collection, followed by descriptive statistical analysis through the presentation of bar charts and statistical summaries that include minimum, maximum, average, standard deviation, and coefficient of variation to describe the characteristics of the data. Furthermore, multiple linear regression modeling (Ordinary Least Squares/OLS), determination of spatial weighting matrix (W), and assumption testing in the form of multicollinearity tests were carried out. If multicollinearity is not found, the analysis is followed by a spatial autocorrelation test using Moran's I and Local Indicators of Spatial Association (LISA). If there is no spatial autocorrelation, the OLS model is set as the final model. On the other hand, if spatial autocorrelation is found, a Lagrange Multiplier (LM) test is carried out to determine the most suitable spatial regression model, namely Spatial Autoregressive (SAR) or Spatial Error Model (SEM). The final stage of the research includes the interpretation of the best model, the identification of variables that have a significant effect on the poverty level in Lampung Province, the preparation of research flow charts, the scheduling of research activities, and the drawing of conclusions based on the results of the analysis obtained.

III. RESULT AND DISCUSSION

Autoregressive Model *(SAR) Spatial* Fit Test Using *Rook Conjunctivitis Weighting Matrix*

The Spatial Autoregressive *(SAR) model match test* in this study was carried out using *the Wald* test and *the rho* parameter (). Based on the results of the model parameter estimation in Table 4.12, the spatial coefficient value ρ*rho* () is 0.38130 with ρ*a p-value* of 0.021307, which shows that the spatial influence is significant at the level = 5 %. This means that the poverty level of a regency/city in Lampung Province is influenced by the poverty of the neighboring regency/city, so there is a strong spatial relationship in the model. Thus, the spatial relationship in the data has been proven and the use of α*the Spatial Autoregressive* (SAR) model in this study is appropriate. Furthermore, the results of the residual LM test produced a *p-value* of 0.50493, which means that there is no spatial autocorrelation in the residual model. This condition shows that the SAR model has succeeded in capturing the spatial influence previously found in the OLS model. Overall, these results confirm that the SAR model has met the model fit assumptions and is feasible for use in further analysis.

Test the Significance of *Autoregressive Model* (SAR) Spatial Parameters Using the *Contiguity Rook Weighting Matrix*

Based on the SAR model equation in the Table, it is obtained that the value of the coefficient *rho* () by 0.38130, z-test (ρ*p-value* 0.021307), as well as the Wald test (*p-value* 0.021307) which shows the spatial influence of the distribution of poverty in Lampung Province. This shows that the number of poor people in a regency/city is influenced by poverty conditions in the adjacent regency/city. (WY)

Thus, an increase in the number of poor people in neighboring areas will encourage an increase in the number of poor people in the area. The percentage of economic growth (X_1)has a coefficient of -3.75246 with *a p-value* of 0.643128, which shows that the percentage of economic growth(X_1) has no effect on poverty in Lampung Province. The labor force participation rate with a coefficient $(X_2)$of -0.94903 and *a p-value* of 0.932, shows that the labor force participation rate (X_2)does not have a significant effect on poverty. Meanwhile, the number of poor people (X_3) and the human development index were obtained with a coefficient value $(X_4)$of 0.10865 with *a p-value* of <2.2e-16 and a coefficient value of -4.15231 with *a p-value* of 0.021307 which shows that the number of poor people (X_3) and the human development index have a significant effect on poverty. Thus, the population and human development index have a significant effect on poverty in Lampung Province. In addition to demographic factors and the quality of human development, spatial factors also play an important role in poverty between districts/cities in Lampung Province so that the use of the SAR model is appropriate for this data. (X_4)

Spatial Autoregressive Model *(SAR)* Residual Autocorrelation Test

Residual autocorrelation tests were performed to see if there were still residual spatial linkages after the *Spatial Autoregressive Model* (SAR) model was applied. The test was carried out using *Morans'I* and LISA on the residual model.

Table 1. Residual Autocorrelation Test

Test Statistics	Value
Morans'I	0.1038
Expectation Value	-0.0714
Variance	0.0235
Z-value	1.1428
p-value	0.1266
Test Results	No residual autocorrelation

Based on the table, a *p-value* of 0.1266 was obtained so that at a significant level of 10%, it can be concluded that there is no spatial autocorrelation in the residual SAR model. Morans*'I's* value of 0.1038 which is close to zero also indicates that the residuals are random and do not follow a specific spatial pattern. Thus, the SAR model used has successfully overcome spatial dependencies in the data, so that the resulting residual is free from spatial influences and the model can be said to have met the feasibility as a spatial model. To provide a visual overview of the distribution pattern of the SAR model estimate, a residual SAR map of Lampung Province is presented. On the SAR residual map of Lampung Province, color variations represent the size of the residual value in the Regency/City. Blue indicates areas with positive residual or higher poor populations, while reddish indicates areas with lower poor populations. Meanwhile, the color that is close to white shows that the model's estimated results are close to the condition of the Lampung Province area. The color patterns on the SAR residual maps are scattered and do not form specific geographic clusters, which confirms that the SAR model is more effective, the remaining errors in the model are random and local, and are no longer affected by the spatial proximity between regions.

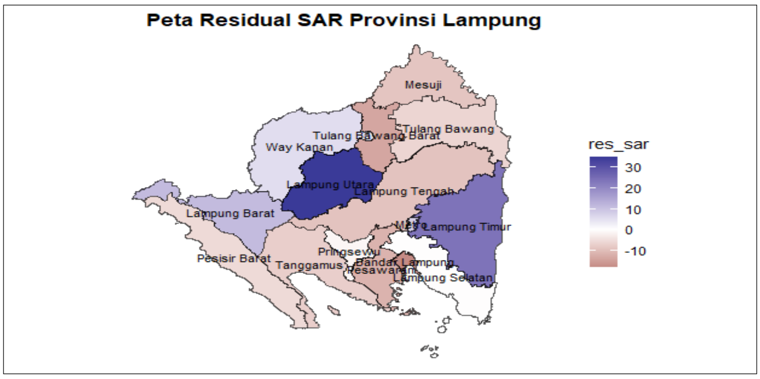

Fig. 1. SAR Residual Map

Autoregressive Model *(SAR)* *Spatial* Model Assumption Test

The SAR model assumption test was carried out to find out whether the SAR model obtained was good. The following are the results of the assumption test on the SAR model.

Table 2. SAR Model Assumption Test

Assumption Test	*p-value*
Normality	0.0872
Homoskedasticity	0.2754

Based on the results of the normality assumption test using *Shapiro-Wilk* , a *p-value* of 0.0872 was obtained greater than the significant level of 5%, it can be concluded that the residual is normally distributed. And in the homocedasticity test using *Breusch-Pagan* , a *p-value* of 0.2754 was obtained greater than the significant level of 10%, it can be concluded that homocedasticity did not occur. So it can be concluded that the assumption of the SAR model is fulfilled.

Spatial Error Model *(SEM)* Modeling

Based on the LM test, the most appropriate model is *Spatial Autoregressive Model* (SAR), The researcher still displays the results of parameter estimation *Spatial Error Model* (SEM) as a comparison to strengthen the process of selecting the best model.

Table 3. SEM Model Parameter Estimation

Parameters	Estimation	Std. Error	$z - value$	*p-value*
Intercept	210.2727	128.7532	1.6331	0.1024
$\mathbf{X_1}$	-4.2703	9.0059	-0.4742	0.6354
$\mathbf{X_2}$	-0.9185	1.1456	-0.8018	0.4227
$\mathbf{X_3}$	0.1057	0.0114	9.2972	<0.0001*
$\mathbf{X_4}$	-1.8312	1.4203	-1.2893	0.1973
$\boldsymbol{\lambda}$ (***lamda***)	-0.0854	0.35806	-0.2385	0.81149
		AIC = 139.50		

Description :*) Significant at = 10 %α

Based on the results of the estimation of the parameters of the SEM model pad table 4.16, the SEM model equations obtained are:

$$\hat{y} = 210.27 - 4.2703\ \mathrm{X}_1 - 0.9185\ \mathrm{X}_2 + 0.1057\ \mathrm{X}_3 - 1.8312\mathrm{X}_4$$

With spatial errors:

$$u = -0.0854\ Wu + \varepsilon$$

Model estimation results *Spatial Error Model* (SEM), it is obtained that the value of the coefficient *Lamda* by -0.0854 with *p-value* of 0.81149 so that it is not significant at the level of 10%. This means that there is no influence *Spatial Error* data, so SEM is not appropriate to be used in this study. The AIC value of the SEM model is 139.50, which is greater than the SAR model.

Best Model Selection

The selection of the best model was carried out to see the accuracy of the use of spatial regression models on the number of poor people in Lampung Province using the value of *Academic Information Criteria* (AIC).

Table 4. AIC Values

Models	AIC
SEM	139.5049
OLS	137.5154
SAR	136.3521

Based on the results of the measurement of the model's goodness using AIC in the *Spatial Error Model* (SEM) of 139.5049. For the OLS model, an AIC value of 137.5154 was obtained. For *the Spatial Autoregressive* (SAR) model, it is 136.3521. Therefore, it can be concluded that the method chosen to analyze the number of poor people in Lampung Province is *Spatial Autoregressive* (SAR). From these equations can be described in a region. Two areas will be taken, namely East Lampung and Central Lampung Regencies. This election is because East Lampung and Central Lampung have a high number of poor people. So it is hoped that it can help the pattern of the distribution of the number of poor people in East Lampung and Central Lampung. Here are the models obtained:

1. East Lampung Regency has a region code 06 which borders Central Lampung Regency with code 05, Metro Regency with code 02, South Lampung with code 04, and Tulang Bawang with code 14, So the alleged spatial regression equation obtained is as follows:

$$\hat{y}_{06} = -344.20034 + 0.10865\, x_{06,1} - 4.15231\, x_{06,2} + u_{06}$$

$$u_{\text{Lampung Timur}} = 0.07626\, u_{\text{Lampung Tengah}} + 0.07626\, u_{\text{Lampung Selatan}} + 0.07626\, u_{\text{Tulang Bawang}} + 0.07626\, u_{\text{Metro}}$$

2. Central Lampung Regency has a region code 05 which borders West Lampung Regency with code 03, Metro with code 02, South Lampung with code 04, East Lampung with code 06, North Lampung with code 07, Pesawaran with code 09, Pringsewu with code 11, Tanggamus with code 12, Tulang Bawang Barat with code 13, and Tulang Bawang with code 14. So that the approximate spatial regression equation obtained is as follows:

$$\hat{y}_{05} = \text{- } 344.20034 + \text{- } + 0.10865\ {}_{01,1} 4.15231\ {}_{05,2}\ u_{05}$$

The equation is a spatial regression model obtained from the Spatial Error Model (SEM) approach for the 05th region. The value shows the estimated number of poor people in the region, while it is a variable of Economic Growth (GDP) and is the Labor Force Participation Rate (TPAK). The constant of −344.20034 indicates the basic value of the number of poor people when all free variables are zero. The regression coefficient of the Economic Growth (GDP) variable of 0.10865 indicates that every increase of one unit of GDP, assuming that other variables are constant, will increase the estimated number of poor people by 0.10865 units. This result shows that the economic growth that has occurred has not been fully inclusive so that the benefits of economic development have not been felt equally by all levels of society. Conversely, the TPAK coefficient of −4.15231 indicates that any increase in the labor force participation rate by one percent will decrease the number of poor people by 4.15231 units, assuming other variables remain the same. These findings indicate that the higher the involvement of the population in the job market, the greater the opportunity for people to earn income, so that the poverty rate tends to decrease. $\hat{y}_{05} X_{05,1} X_{05,2}$

In the context of the study "Spatial Inequality of Poverty in Lampung Province in the Perspective of Sustainable Development Using Autoregressive Spatial Approach and Spatial Error Model", the existence of a spatial error component () shows that poverty variation in a district/city is not only influenced by the characteristics of the region, but also by factors originating from the surrounding area that are not explicitly included in the model. This indicates a spatial dependence on the error component, so that social, economic, and development policy characteristics in neighboring districts/cities also affect the poverty conditions of a region. Thus, the Spatial Error Model (SEM) approach is able to capture spatial influences that cannot be explained by ordinary linear regression models (OLS), thereby producing more accurate estimates in explaining the pattern of poverty inequality in Lampung Province. From the perspective of sustainable development, these results confirm that poverty alleviation efforts are not enough to be carried out partially in each district/city, but require coordination of development policies between regions so that the impact of economic development, increased employment opportunities, and equitable distribution of welfare can be felt more evenly throughout Lampung Province.u_{05}

IV. CONCLUSION

The model shows a significant spatial influence, where the poverty level in a district/city is not only influenced by the characteristics of the region itself, but also by the poverty conditions in the adjacent areas. Thus, the SAR model is able to provide an overview of the inter-regional relationship in poverty patterns so that it can be used as a basis for the preparation of poverty alleviation policies that are more targeted, integrated, and oriented towards sustainable development in Lampung Province.

The results of spatial autocorrelation analysis using Moran's I and Local Indicators of Spatial Association (LISA) show that the spatial pattern of the number of poor people in Lampung Province has different characteristics between regions. Areas with high positive residuals, such as North Lampung and East Lampung Regencies, indicate that the number of poor people in these areas is higher than the model's predicted value. In contrast, areas with negative residuals, such as Mesuji Regency, Tulang Bawang, and some coastal areas, showed lower numbers of poor people than the model's predicted results. In addition, most areas in the central and southern parts of Lampung Province have near-zero residuals, which suggests that the model's predictions are close to the actual conditions. Scattered residual patterns that do not form specific spatial groupings indicate that the SAR model has managed to capture spatial dependence on poverty data, so that the resulting residual residue can be considered a random variation that is no longer affected by spatial relationships between regions.

Based on the results of the SAR model estimation, there are two variables that have a significant effect on the number of poor people in Lampung Province, namely the number of people (X_3) and the Human Development Index (HDI) (X_4). In contrast, the percentage of economic growth (X_1) and the labor force participation rate (TPAK) (X_2) did not show a significant effect on the number of poor people. In addition, a significant spatial coefficient value of rho (ρ) shows that poverty inequality in an area is influenced by poverty conditions in adjacent areas, thus proving the existence of a spatial spillover effect in the distribution of poverty in Lampung Province. Meanwhile, the Spatial Error Model (SEM) model was not chosen as the best model because the lambda parameter (λ) was not significant, indicating that the spatial dependency did not occur on the error component, but directly on the dependent variable. Therefore, the SAR model is considered more appropriate in explaining the spatial inequality of poverty in Lampung Province and provides a stronger basis in the formulation of sustainable and regional-based development policies.

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