

Modeling the Economic Growth Rate in South Sulawesi Province Using a Spatial Analysis Approach

Adiatma^{1*}, Risnawati Ibtnas², Endang Astuti³

^{1,2,3} *Mathematics Study Program, Universitas Islam Negeri Alauddin Makassar, Gowa, Indonesia*

*Corresponding author: adiatma.rasyid@uin-alauddin.ac.id

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ABSTRACT

Economic growth is one of the indicators used to measure the success of regional development. The economic growth rate in South Sulawesi Province is influenced by several socioeconomic factors and may exhibit spatial effects among regions. This study aims to model the economic growth rate in South Sulawesi Province using a spatial analysis approach and to identify the factors that significantly affect economic growth in 2023. The data used are secondary data obtained from the Central Bureau of Statistics (BPS) of South Sulawesi Province, covering 24 districts/cities. The explanatory variables include the open unemployment rate, poverty rate, expected years of schooling, labor force participation rate, average years of schooling, and population. Spatial analysis was conducted using the Spatial Error Model (SEM) based on the Queen Contiguity spatial weight matrix. The results show that the SEM is the most appropriate model for describing the economic growth rate in South Sulawesi Province. The expected years of schooling and labor force participation rate significantly affect the economic growth rate, while the spatial error coefficient indicates the presence of spatial dependence among districts/cities in South Sulawesi Province.

KEYWORDS

Economic Growth Rate, Spatial Analysis, Spatial Error Model, Queen Contiguity, South Sulawesi Province.

1. INTRODUCTION

Economic growth is one of the indicators used to measure the success of regional development because it reflects improvements in production capacity, national income, and community welfare [1]. Sustainable economic growth is closely related to employment creation, poverty reduction, and improvements in living standards.

According to data from the Central Bureau of Statistics (BPS) of South Sulawesi Province, the economic growth rate of South Sulawesi declined from 5.09% in 2022 to 4.51% in 2023 [2]. This decline indicates the existence of structural economic problems that require further investigation to identify the factors affecting economic growth in the region.

Several factors are suspected to influence economic growth, including the Open Unemployment Rate (OUR), Poverty Rate, Expected Years of Schooling (EYS), Mean Years of Schooling (MYS), Labor Force Participation Rate (LFPR), and Population. These factors vary across districts and cities and may lead to differences in regional economic performance [3, 4].

Regional economic analysis should also consider spatial aspects because the economic condition of a region may be influenced by neighboring regions. Geographical interactions among regions can lead to spatial autocorrelation, causing the independence assumption of classical regression models to be violated. Therefore, spatial regression approaches are needed to accommodate spatial dependence and interregional relationships in modeling economic growth [5].

Previous studies have demonstrated the importance of spatial approaches in regional economic analysis. Hastuti and Sukartini [6] found that spatial factors significantly affected economic growth in Maluku Province, while Weni et al. [7] identified regional clustering based on economic growth levels in West Sumatra. However, studies on modeling the economic

growth rate of districts and cities in South Sulawesi Province using spatial regression approaches remain limited.

Therefore, this study aims to model the economic growth rate of districts and cities in South Sulawesi Province in 2023 using a spatial analysis approach and to identify the factors that significantly affect economic growth through the application of spatial regression models.

2. LITERATURE REVIEW

2.1 Multiple Linear Regression

Multiple linear regression is a statistical method used to analyze the relationship between one dependent variable and several independent variables simultaneously. This method aims to determine the effect of explanatory variables on the response variable and to estimate the contribution of each predictor to the model [8]. The general form of the multiple linear regression model is expressed as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (1)$$

where Y is the dependent variable, $X_1, X_2, \dots, X_k$ are the independent variables, β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_k$ are the regression coefficients, and ε is the random error term.

2.2 Spatial Analysis

Spatial analysis is an analytical approach that considers geographical locations and interactions among neighboring regions. Spatial data contain both attribute information and geographical information, allowing researchers to identify spatial patterns and dependencies that cannot be explained by conventional statistical methods [9]. In regional economic studies, spatial analysis is important because the economic condition of a region may be influenced by neighboring regions, leading to spatial dependence among observations.

2.3 Spatial Weight Matrix

A spatial weight matrix describes the neighborhood relationships among spatial units. In this study, the Queen Contiguity approach was employed because neighboring regions are defined as regions sharing either a common boundary or a common vertex [9]. The spatial weight matrix is defined as

$$w_{ij} = \begin{cases} 1, & \text{if regions } i \text{ and } j \text{ are neighbors,} \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

where w_{ij} denotes the spatial weight between regions i and j . The matrix is then row-standardized so that the sum of each row equals one.

2.4 Spatial Autocorrelation and Moran's I

Spatial autocorrelation refers to the correlation of observations based on their geographical locations [10]. Positive spatial autocorrelation indicates that neighboring regions tend to have similar values, whereas negative spatial autocorrelation indicates dissimilar values among neighboring regions.

Moran's I statistic is widely used to detect spatial autocorrelation and is defined as

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^n \sum_{j=1}^n w_{ij} \right) \left(\sum_{i=1}^n (x_i - \bar{x})^2 \right)} \quad (3)$$

The expected value of Moran's I is

$$E(I) = \frac{-1}{n-1} \quad (4)$$

and the test statistic is

$$Z = \frac{I - E(I)}{\sqrt{\text{Var}(I)}} \quad (5)$$

The null hypothesis states that there is no spatial autocorrelation among regions, whereas the alternative hypothesis indicates the presence of spatial autocorrelation.

2.5 Spatial Regression and Spatial Error Model

Spatial regression is an extension of classical regression that incorporates spatial dependence among observations [9]. The general spatial regression model is expressed as

$$y = \rho Wy + X\beta + u \quad (6)$$

$$u = \lambda Wu + \varepsilon \quad (7)$$

where y is the response variable vector, X is the explanatory variable matrix, W is the spatial weight matrix, ρ is the spatial lag coefficient, λ is the spatial error coefficient, and ε is the random error vector.

The Lagrange Multiplier (LM) test is commonly used to determine the appropriate spatial regression model [11]. When spatial dependence occurs in the error term, the Spatial Error Model (SEM) is employed. The SEM is formulated as

$$Y = X\beta + u \quad (8)$$

$$u = \lambda Wu + \varepsilon \quad (9)$$

where the error term of one region may be influenced by the errors of neighboring regions [12].

3. METHODOLOGY

This study employed quantitative data obtained from secondary sources, namely publications of the Central Bureau of Statistics (BPS) of South Sulawesi Province in 2023. The observational units consisted of 24 districts and cities in South Sulawesi Province. The response variable was the economic growth rate (Y), while the explanatory variables consisted of the Open Unemployment Rate (X_1), Poverty Rate (X_2), Expected Years of Schooling (X_3), Labor Force Participation Rate (X_4), Mean Years of Schooling (X_5), and Population (X_6).

3.1 Research Procedure

The research procedure consists of the following steps:

1. Conducting descriptive statistical analysis.
2. Constructing a multiple linear regression model and performing classical assumption tests.
3. Constructing a spatial weighting matrix using the Queen Contiguity approach.
4. Performing Moran's I test to identify spatial autocorrelation.
5. Conducting the Lagrange Multiplier (LM) test to determine the appropriate spatial regression model.
6. Estimating the Spatial Error Model (SEM).
7. Interpreting the results and drawing conclusions.

4. RESULT & DISCUSSION

4.1 Descriptive Analysis of Research Variables

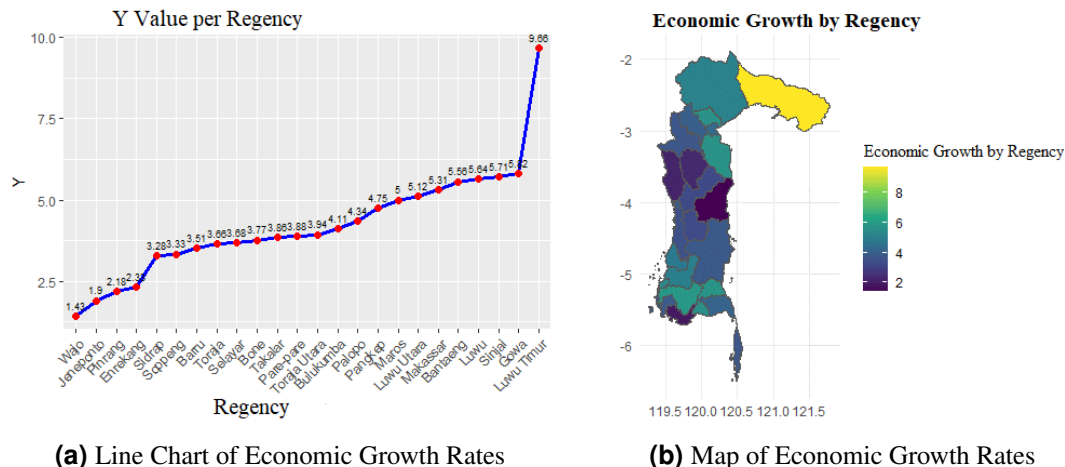
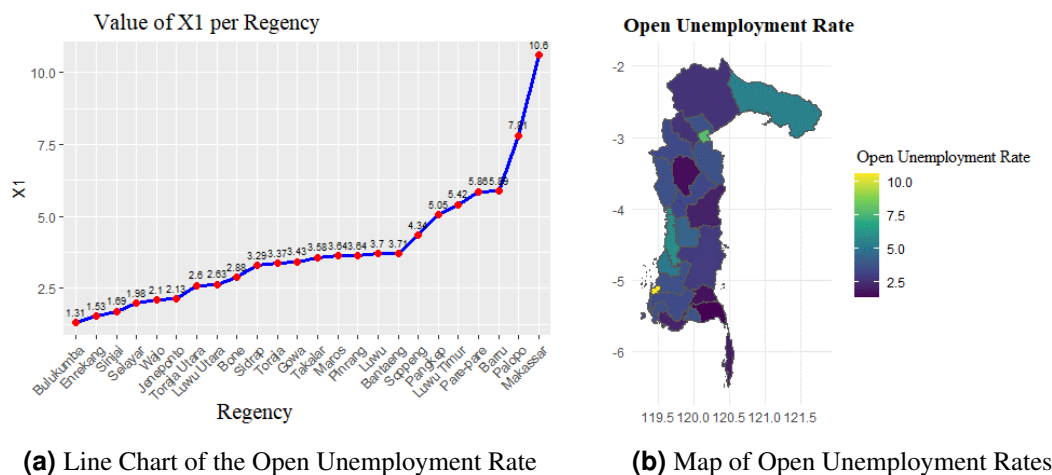
The results of the descriptive statistics for the research variables are presented in **Table 1**.

Based on **Table 1**, each variable exhibits different data distribution characteristics. Variables Y and X_1 show relatively smaller variation compared to X_2 and X_6 , which have a wider range of values, indicating significant differences in conditions across regions for these two variables.

To clarify the data distribution patterns, line charts and distribution maps were shown in **Figure 1 to 7** for each research variable.

Table 1. Results of Descriptive Statistical Analysis

Variable	Minimum	Q_1	Mean	Q_3	Maximum	Variance
Y	1.430	3.465	4.240	5.168	9.660	1.685
X_1	1.310	2.482	3.841	4.518	10.600	2.132
X_2	7.98	17.42	32.87	42.11	80.32	19.322
X_3	12.12	12.95	13.39	13.64	15.61	0.808
X_4	55.49	62.58	66.99	69.72	82.35	6.119
X_5	7.000	7.973	8.519	8.633	11.560	1.136
X_6	141.2	237.3	390.1	409.6	1455.0	282.314

**Figure 1.** Line Chart and Map of Economic Growth Rates**Figure 2.** Line Chart and Map of Open Unemployment Rates

4.2 Multiple Linear Regression Analysis

1. Normality Test

The Shapiro-Wilk test resulted in a p-value of 0.2678. Since the p-value is greater than the significance level of 0.10, the residuals are normally distributed.

2. Multicollinearity Test

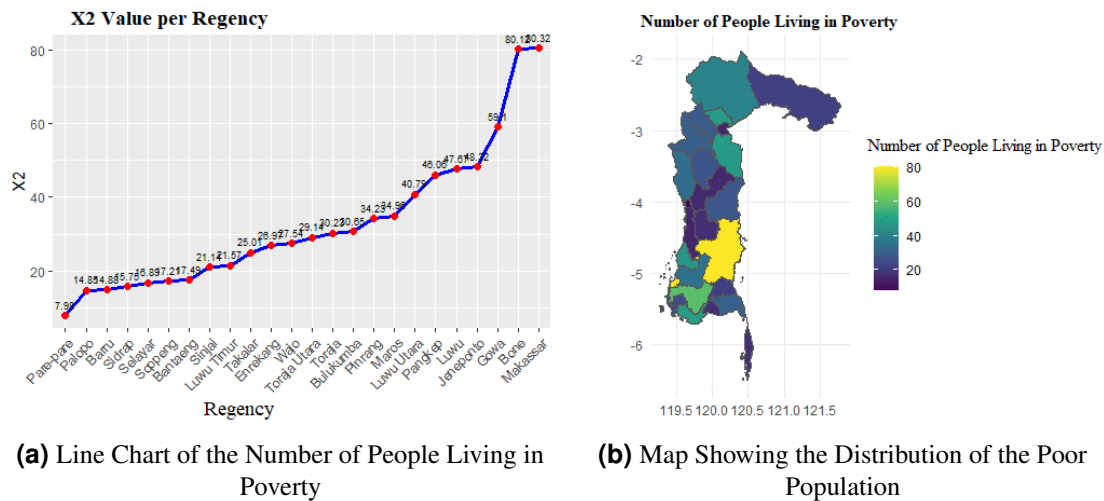


Figure 3. Line Chart of the Number of People Living in Poverty and Map Showing the Distribution of the Poor Population

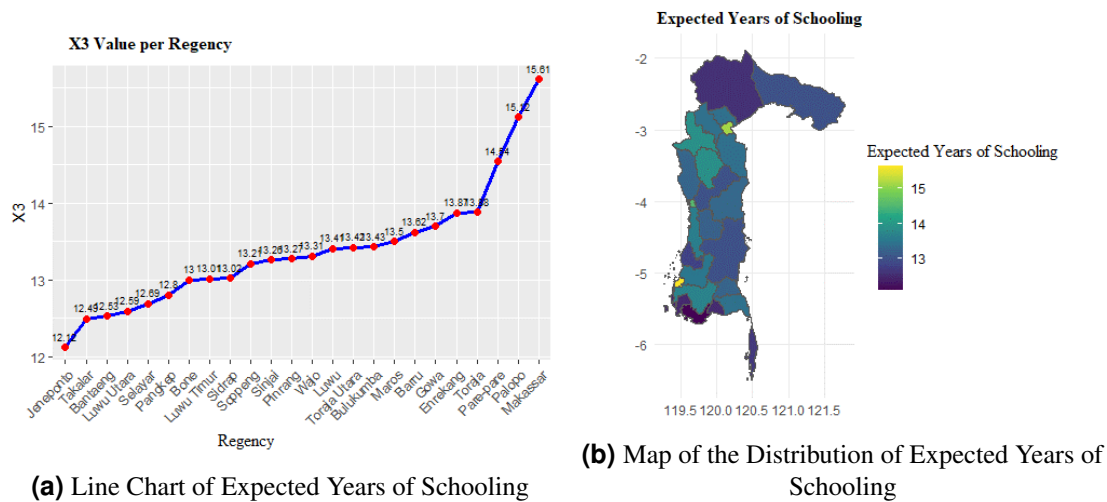


Figure 4. Line Chart and Map of Expected Years of Schooling

The Variance Inflation Factor (VIF) values of all explanatory variables were less than 10, indicating that multicollinearity was not present in the model.

3. Heteroscedasticity Test

The Breusch-Pagan test produced a p-value of 0.8877, which is greater than 0.10. Therefore, the assumption of homoscedasticity was satisfied.

4.3 Spatial Autocorrelation Test

The Moran's I statistic was employed to identify the presence of spatial dependence among districts and cities in South Sulawesi Province.

The results showed that the economic growth rate (Y) had a Moran's I value of 0.19850 with a Z-statistic of 1.8269. Furthermore, the Labor Force Participation Rate (X_4) had a Z-statistic of 2.1695. Since both values exceed the critical value of 1.645 at the 10% significance level, positive spatial autocorrelation exists among the observations. This finding indicates that neighboring districts and cities tend to have similar economic growth characteristics and labor force participation rates.

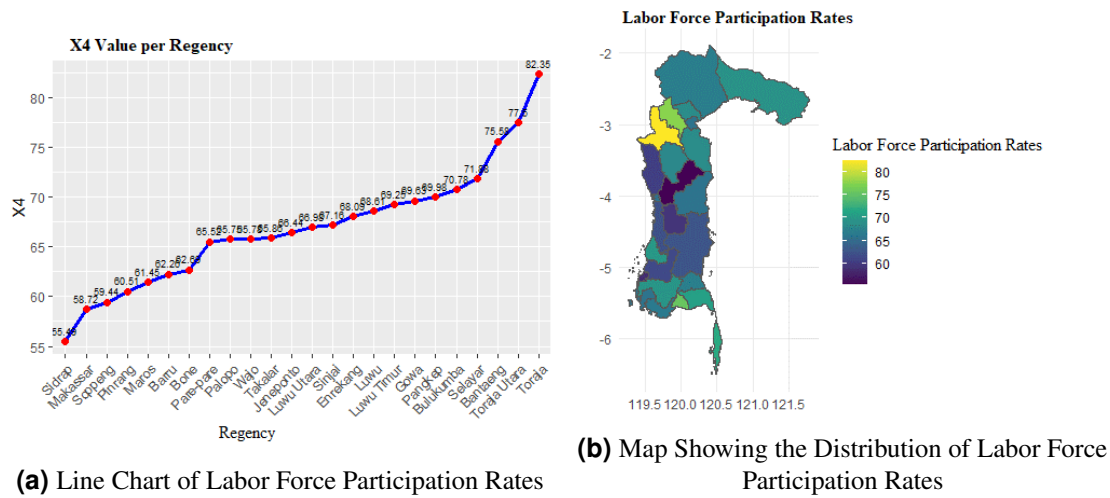


Figure 5. Line Chart and Map of Labor Force Participation Rates

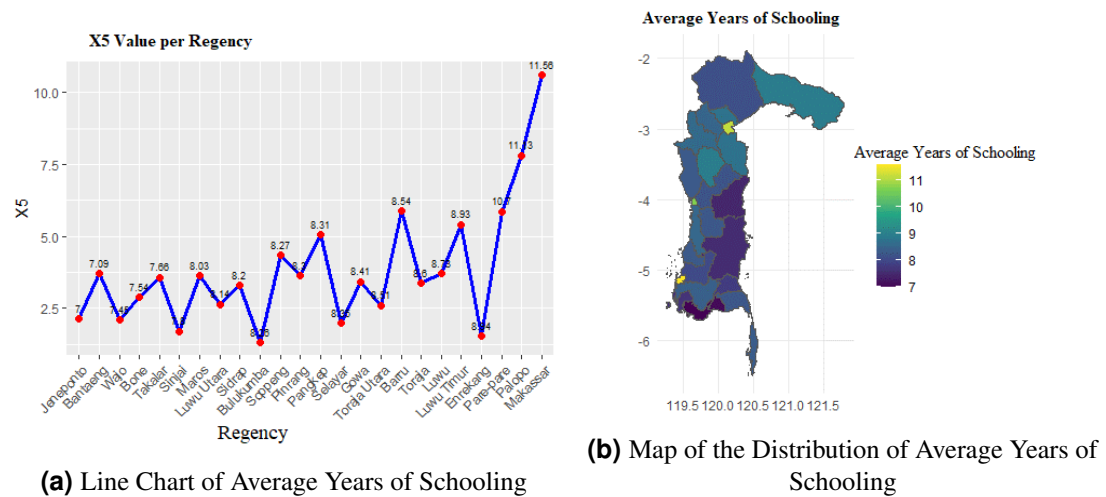


Figure 6. Line Chart and Map of Average Years of Schooling

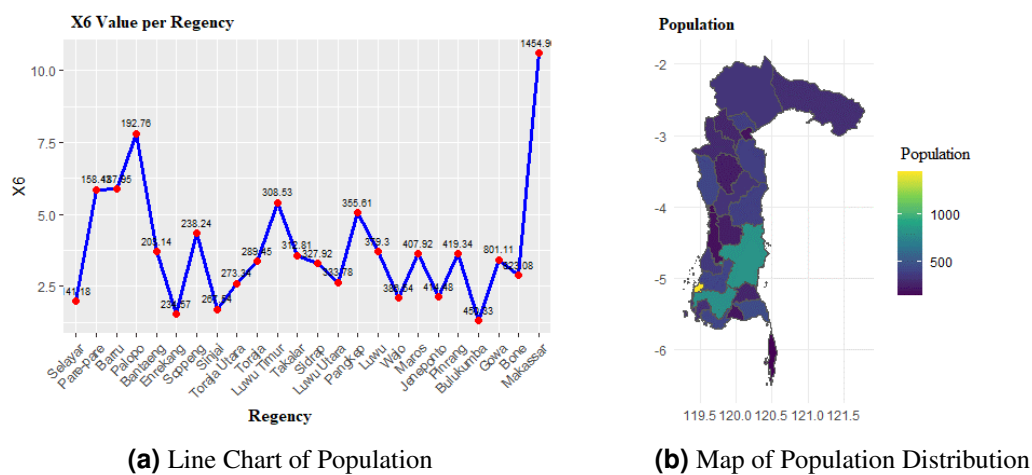


Figure 7. Line Chart and Map of Population Distribution

4.4 Lagrange Multiplier Test

The Lagrange Multiplier (LM) test was conducted to determine the appropriate spatial regression model. The adjusted LM-error statistic produced a p-value of 0.09509, which is less than the significance level of 0.10. Therefore, the Spatial Error Model (SEM) was selected as the appropriate model for explaining the economic growth rate in South Sulawesi Province.

4.5 Spatial Error Model (SEM)

The estimated Spatial Error Model is given by

$$\hat{Y} = 14.5200 + 0.3248X_1 - 0.0225X_2 - 2.2141X_3 + 0.1128X_4 + 1.1551X_5 + 0.0039X_6$$

$$\lambda = 0.4653$$

The estimation results indicate that Expected Years of Schooling (X_3) has a significant negative effect on the economic growth rate, while the Labor Force Participation Rate (X_4) has a significant positive effect. In addition, Mean Years of Schooling (X_5) is significant at the 10% significance level.

The significant value of the spatial error coefficient indicates the presence of spatial dependence in the error term, implying that unobserved factors affecting economic growth in one region are associated with those in neighboring regions.

5. DISCUSSION

The positive effect of the Labor Force Participation Rate suggests that increased participation of the working-age population in economic activities contributes to higher economic growth. Conversely, the negative coefficient of Expected Years of Schooling indicates that improvements in educational expectations have not yet been fully translated into higher regional productivity. Furthermore, the significance of the spatial error parameter confirms that economic growth in South Sulawesi is not independent across regions. Economic conditions in one district or city are influenced by conditions in neighboring regions, emphasizing the importance of incorporating spatial effects in regional economic modeling.

6. CONCLUSION

Based on the results of the study, the economic growth rate in South Sulawesi Province in 2023 was best modeled using the Spatial Error Model (SEM), which is expressed as

$$\hat{Y}_i = 14.5200 + 0.3248X_{1i} - 0.0225X_{2i} - 2.2141X_{3i} + 0.1128X_{4i} + 1.1551X_{5i} + 0.0039X_{6i} + u_i$$

$$u_i = 0.4653 \sum_{j=1, j \neq i}^{24} w_{ij}u_j + \varepsilon_i$$

The results of the spatial error estimates reveal that variables X_3 (Expected Years of Schooling), X_4 (Labor Force Participation Rate), and X_5 (Average Years of Schooling) significantly drive economic growth in South Sulawesi. These findings indicate that regional economic conditions are also influenced by spatial interactions with surrounding areas.

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