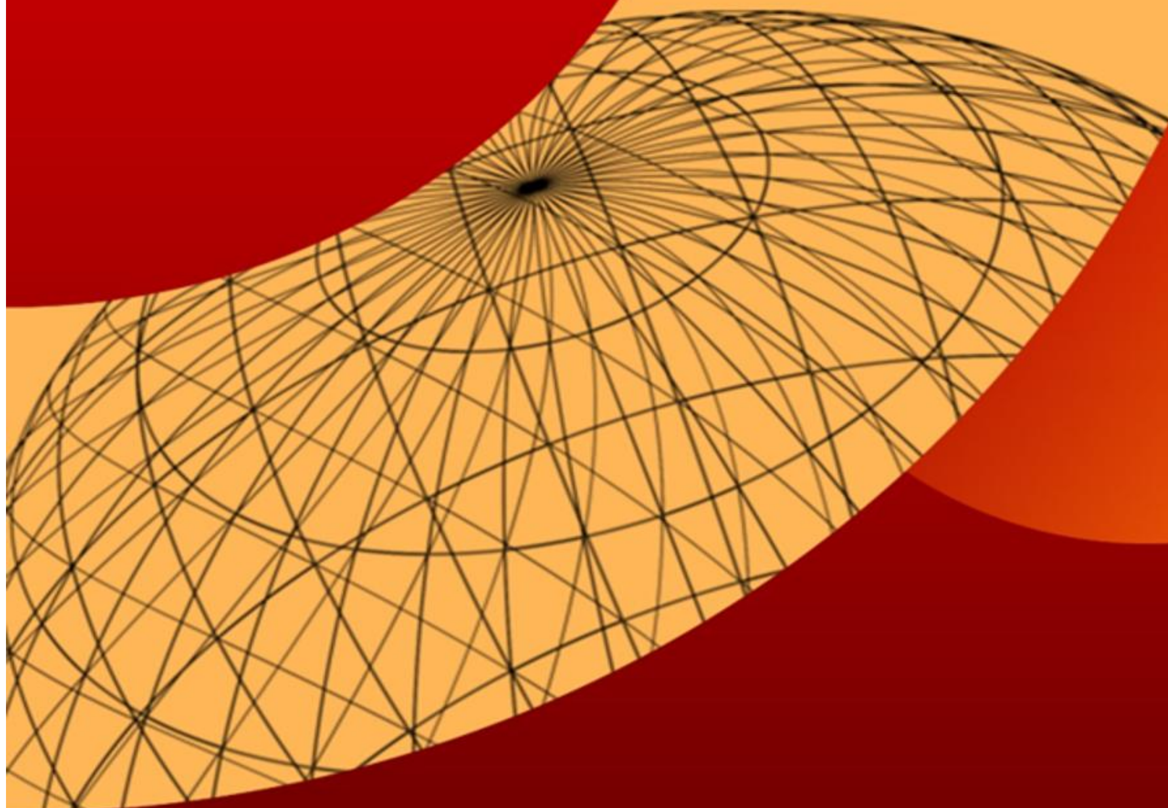
April 2026
Volume 7 Nomor 1

p-ISSN 2723-0325 e-ISSN 2723-0333



TENSOR

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TENSOR Pure and Applied Mathematics Journal

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Published by:

Department of Mathematics,
Faculty of Mathematics and Natural Sciences,
Pattimura University.
Ambon
2026

TENSOR
Pure and Applied Mathematics Journal
Volume 7 Number 1 | April 2026

Publisher
Department of Mathematics,
Faculty of Mathematics and Natural Sciences,
Pattimura University, Ambon, Indonesia

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Volume 7 Number 1 | April 2026

TENSOR
Pure and Applied Mathematics Journal

TENSOR Pure and Applied Mathematics Journal
April 2026 | Vol. 7 | No. 1 Page 27–42
p-ISSN: 2723-0325 e-ISSN: 2723-0333

Application of the Spatial Durbin Model (SDM) to Analyze the Factors Affecting Poverty in Maluku Province in 2024

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Manuscript submitted : May 2026;
Accepted for publication : June 2026.
DOI : https://doi.org/10.30598/tensorvol4iss1pp27-42

Abstract: Poverty is defined as a condition in which individuals are unable to meet the minimum basic needs necessary for a dignified life. In Indonesia, particularly in Maluku, poverty remains a critical problem, exacerbated by the low quality of human resources and limited access to education, health care, and employment opportunities. This study aims to analyze the factors that significantly influence poverty in Maluku Province in 2024 and to build a poverty model using the Spatial Durbin Model (SDM). This research applies a statistical method known as the Spatial Durbin Model (SDM), which is a development of the Spatial Autoregressive Model (SAR). Thus, this model not only includes spatial lag on dependent variables, but also includes spatial lag on independent variables. Based on the calculations, it was found that the factors that significantly influence poverty are the average length of schooling (X_2) and the labor force participation rate (X_3). An R^2 value of 96.46% and an AIC of 54.831 indicate that the model SDM provides good results in explaining the poverty variations in Maluku Province.

2010 Mathematical Subject Classification: 37M10
Keywords: Poverty in Maluku, Spatial Regression, Spatial Durbin Model (SDM)

1. Introduction

Poverty can be defined as a state in which a person is unable to meet the minimum basic needs necessary to live a decent and dignified life [1]. Defining poverty is not an easy thing, because poverty has various dimensions. Therefore, understanding poverty needs to involve various aspects, such as access to education, health, employment, and social services. In addition, factors such as geographical location, culture, and economic conditions also play an important role in determining a person's poverty level. By comprehensively understanding poverty, more effective policies can be designed to address these problems and improve people's quality of life.

Poverty, according to Bappenas, refers to a situation in which a person or a group of people do not have sufficient ability to meet the basic needs that are their basic rights, such as food, clothing, shelter, education, and health services [2]. This inability hinders them from living a decent life and developing themselves optimally as dignified human beings.

Poverty is a fundamental problem faced by various countries in the world, especially developing countries such as Indonesia. In Indonesia, poverty is a phenomenon that often occurs and is part of the complexity of development challenges. One of the main causes of this problem is the low quality of human resources, which directly affects the lack of the level of community welfare [3]. Poverty is a problem that must be handled by the government, so the government has made various efforts to overcome the problem of poverty, especially in areas such as Maluku which are still facing considerable development challenges.

Maluku is a region in Indonesia located in eastern Indonesia. Unfortunately, Maluku is one of the poorest provinces in Indonesia. Based on data released by the Central Statistics Agency (BPS), the percentage of poor people in Maluku has decreased from 297.68 thousand people to 293.99 thousand people or 15.78 percent in September 2024. Despite the decline, Maluku is still in eighth place as the poorest province in Indonesia, with a poor population of around 293.99 thousand people. This decrease was recorded at 3.69 thousand people against March 2024, which shows an improvement in people's economic conditions [4].

One of the efforts that can be made to overcome the problem of poverty is through an in-depth study of various significant factors that contribute to it, such as low education levels, limited access to health, and economic inequality, thus allowing for the formulation of more targeted and sustainable government policies in the future. Statistical methods such as regression analysis can be used to create models that estimate the relationship between poverty levels and their causative factors, thus helping to find patterns and how strong those relationships are. Because areas with high poverty rates are often geographically close together, data analysis should consider spatial factors or the relationship between regions through the spatial regression method, in order to avoid miscalculations and capture the effects of poverty distribution between these regions.

One of the spatial regression models used is the Spatial Durbin Model (SDM), introduced by [5]. This method uses spatial area data as its approach. So the weighting matrix used is a *contiguity* matrix which is based on the intersection between observed locations. In the HR method, spatial lag is accounted for not only on dependent variables (Y), but also on independent variables (X). The purpose of the application of SDM is to analyze the more accurate spatial relationship between poverty factors and the impact of spillover between regions, significantly different from Spatial Autoregressive (SAR) which only considers spatial lag in dependent variables so that it is less able to capture the effects of the spread of independent variables such as education and economy. From this description, a problem can be formulated, namely how to identify the factors that affect poverty in Maluku Province by considering the spatial aspect of the location using the SDM method.

Research conducted by [6] regarding the application of the Spatial Durbin Model (SDM) in analyzing factors affecting the percentage of poor people in Cianjur Regency in 2021 showed quite strong results, with R^2 75%. This figure indicates that the model is able to explain 75% of the variation that occurs in poverty data in the region. In the study, it was found that the average length of school and life expectancy at birth are two variables that have a significant influence on poverty levels. Another study conducted by [7] using the Spatial Durbin Model (SDM) method shows that the variables that are indicators in the spread of Covid-19 are the unemployed population and the number of people who have been vaccinated with a result R^2 of 91.11% and MAPE of 24.74%.

Research on poverty with a spatial regression approach has been conducted previously, including in Maluku Province by [8] using specific spatial regression models and different data periods. However, the research is still limited to the use of models such as SAR, SEM and SARMA. Therefore, this study has the novelty of applying the Spatial Durbin Model (SDM) using the latest poverty data, namely September 2024, as well as independent variables that include the GDP growth rate per capita, the average length of schooling, the participation rate of the labor force, and the percentage of the population that is able to capture the direct and indirect influence between districts/cities in Maluku Province.

Based on previous researches, which were conducted using the Spatial Durbin Model (SDM) method, the author is interested in analyzing the factors that affect poverty in Maluku Province in 2024. Through this research, it is hoped that it will be able to provide benefits to the community and the government in order to optimize poverty management in Indonesia, especially Maluku Province, and find suitable solutions so that the Indonesian people are not trapped in the poverty problem.

2. Research Method

In this study, secondary data obtained from the Central Statistics Agency of Maluku Province in 2024 was used. The data includes 11 observation locations, representing all regencies/cities in Maluku Province. The approach used in this study is a quantitative approach.

2.1. Research Variables

The variables used in this study consist of one dependent variable, namely the percentage of the poor population (Y) and four independent variables (X). The following table shows the variables that will be used in this study.

Table 1. Research Variables

Variable	Variable Name
Y	Percentage of Poor Population by Regency/City in Maluku Province in 2024
X_1	Gross Regional Domestic Product Growth Rate per Capita on the Basis of Constant Prices 2010 by Regency/City in Maluku Province (Percent) in 2024
X_2	Average School Length by Regency/City in Maluku Province in 2024
X_3	Labor Force Participation Rate by Regency/City in Maluku Province (Percent) in 2024
X_4	Percentage of Population by Regency/City in Maluku Province in 2024

2.2. Data Analysis Methods

2.2.1 Multiple Regression Linear

Multiple linear regression is an analysis model that uses more than one independent variable to make predictions. A general equation describing multiple linear regression, applied with the Ordinary Least Squares (OLS) method, can be expressed with k independent variables, as described in equations 1 [9]

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i \tag{1}$$

with:

i : $i = 1,2,\ldots,n$ where $n =$ number of observations

k : $k = 1,2,\ldots,p$ where $p =$ number of independent variables

Y_i : observation dependent variable to-i

X_{ik} : independent variables observation to-i dan independent variable to-k

β_0 : constant value

β_k : regression coefficient for variable to-k

ε_i : residual that is assumed to be identical, independent, and normally distributed

2.2.2 Regression Model Assumptions

2.2.2.1 Normality Test

One of the methods used to determine whether the residual of the regression model follows the normal distribution or not is called the normality test. In this test using Shapiro-Wilk with test statistics can be explained as follows [10]:

Hypothesis:

H_0 : data follows normal distribution

H_1 : the data does not follow the normal distribution

Test statistics:

$$W = \frac{\sum_{i=1}^{n}\left(a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}; i = 1,2,3,..,n \tag{2}$$

with:

n : amount of data

a_i : koefisien *Shapiro-Wilk*

x_i : sorted observation data

$\bar{x}$: average observation data

Verdict:

If $W_{\text{count}} > W_{\text{table}}$ or $p - value > \alpha$ and then it fails to refute H_0

2.2.2.2 Heteroskedasticity Test

One of the important assumptions in a regression model that must be met is that the variance of the residual must be constant or fixed, known as homoskedasticity [8]. To identify whether there is a violation of this assumption, or what is known as heteroscedasticity, the Breusch-Pagan test can be used. The hypothesis test used is as follows [11].

Hypothesis:

$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (homoskedasticity)

$H_1 :$ at least one $\sigma_i^2 \neq \sigma^2, i = 1, 2, \ldots, n$ (heteroskedasticity)

Test statistics:

$$BP = \left(\frac{1}{2}\right)\boldsymbol{f}^T\boldsymbol{Z}(\boldsymbol{Z}^T\boldsymbol{Z})^{-1}\boldsymbol{Z}^T\boldsymbol{f} \sim \chi^2_{(\alpha,p-1)} \tag{3}$$

with:

$\boldsymbol{f}$: $(f_1 f_2 f_3)^T$ with $f_i = \left(\frac{e_i^2}{\sigma^2} - 1\right)$

$\boldsymbol{Z}$: normal independent variable vector

e_i : $y_i - \hat{y}$ is residual for observation to-i, $i = 1, 2, \ldots, n$

Verdict:

Reject H_0 if the value $BP > \chi^2_{(\alpha,p-1)}$, p is the number of regression parameters.

2.2.2.3 Multicolinearity Test

A strong correlation between two or more independent variables in a statistical model is called multicollinearity. The symptoms of multicollinearity in a model are detected through VIF (Variance Inflation Factor) analysis. A variable is generally considered to have no multicollinearity problem if the VIF value is less than 10 and the tolerance value is greater than 0.1. VIF values are defined as follows:

$$VIF = \frac{1}{1 - R^2} \tag{4}$$

Value R^2 state how good the relationship is x_j and other independent variables [12].

2.2.2.4 Autocorrelation Test

One of the important assumptions in the regression model is to ensure that the residuals of each observational data must be independent of each other, meaning that there is no relationship or correlation between the residuals in different observations. To detect the relationship between these residuals, autocorrelation testing can be performed, with the most commonly used method being the Durbin-Watson [13] The following are test statistics for the Durbin-Watson (DW) method with the following hypotheses used.

$H_0 : \rho = 0$ (residual is independent)
$H_1 : \rho \neq 0$ (residual is not independent)
The common equations used are as follows.

$$d = \frac{\sum_{i=2}^{n}(\hat{e}_i - \hat{e}_{i-1})^2}{\sum_{i=1}^{n}\hat{e}_i^2} \tag{5}$$

Where $\hat{e}$ is the residual value of the regression. In the Durbin-Watson test, there is a special rule to determine whether or not there is an autocorrelation by comparing two limit values, namely Durbin Upper (DU) and Durbin Lower (DL). The determination of whether or not there is an autocorrelation based on the Durbin-Watson statistical value can be understood through the rules presented in the following table.

Table 2. Uji Durbin-Watson

Statistical value d	Remarks
$\mathbf{0 < d < d_L}$	There is a positive autocorrelation
$\mathbf{d_L < d < d_U}$	No decision
$\mathbf{d_U < d < 4 - d_U}$	No autocorrelation
$\mathbf{4 - d_U < d < 4 - d_L}$	No decision
$\mathbf{4 - d_L < d}$	There is a negative autocorrelation

If the decision obtained is that there is no decision, then a follow up test is required, namely using the Run Test [14]. The hypotheses used are as follows:

H_0 : there is an autocorrelation
H_1 : no autocorrelation
Test statistics:

$$Z = \frac{r - \mu_r}{\sigma_r} = \frac{r - \left(\frac{2n_1n_2}{N} + 1\right)}{\sqrt{\frac{N^2 - 2N}{4(N-1)}}} \tag{6}$$

with:
r : a lot of runs
n_1 : number of group members 1
n_2 : number of group members 2
Decision making:
Reject H_0 if $p - value > \alpha$.

2.2.3 Spatial Weighting Matrix

Spatial weighting matrix or symbolized by $\boldsymbol{W}$ is a matrix of $n \times n$ with non-negative elements. This matrix describes the spatial relationships between regions or locations based on proximity or geographical connectivity. In this context, the matrix $\boldsymbol{W}$ used to determine the weight or degree of interconnectedness between locations, which is generally based on the concept of neighborliness [6].

Each element in the matrix, which is denoted by w_{ij}, represents the relationship between the regions i and j. If the two regions are adjacent to each other or directly intersect, then the $w_{ij} = 1$. On the other hand, if there is no direct relationship between the two, then $w_{ij} = 0$.
In general, the shape of the matrix $\boldsymbol{W}$ can be described as following:

$$\boldsymbol{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{7}$$

with:

$$w_{ij} = \frac{c_{ij}}{\sum_{j=1}^{n} c_{ij}} \tag{8}$$

and:

w_{ij} : standardized weighting matrix values
c_{ij} : the value of the contiguity matrix on the line to-i column to-j; $i, j = 1,2,3, \dots, n$

There are several types of forms of neighborliness according to [15] namely:

1. Rook Contiguity

   The observation area defined by rook contiguity is an area determined based on the sides touching each other, without considering the angles. For example, as shown in Figure 1, spatial units B1, B2, B3, and B4 are considered neighbors of spatial units A.

	Unit B2	
Unit B1	Unit A	Unit B3
	Unit B4	

Fig. 1. Observation Area Rook Contiguity

2. Bishop Contiguity

   The observation area determined by the bishop contiguity is an area determined based on the angles that touch each other, without taking into account the existing sides. For example, as seen in Figure 2, spatial units C1, C2, C3, and C4 are considered neighbors of spatial units A.

Unit C1		Unit C2
	Unit A	
Unit C4		Unit C3

Fig. 2. Observation Area Bishop Contiguity

3. Queen Contiguity

   The observation area designated by queen contiguity is an area determined based on the sides and angles that touch each other. For example, as shown in Figure 3, spatial units B1, B2, B3, B4, C1, C2, C3, and C4, are considered neighbors of spatial units A.

Unit C1	Unit B2	Unit C2
Unit B1	Unit A	Unit B3
Unit C4	Unit B4	Unit C3

Fig. 3. Observation Area Queen Contiguity

In this study, the Queen Contiguity weighting matrix is used because it considers the relationship of proximity between regions which is not only based on side contact but also contact at the angle point between one region and its neighboring region.

2.2.4 Spatial Autocorrelation Test

The thing that must be considered to detect the presence of spatial effects in the data is spatial dependencies. Spatial dependencies describe the relationship between geographically adjacent unit of region, which suggests that the value of a variable in one location can be affected by the value of the same variable in nearby locations. To find out if there is a spatial autocorrelation between locations, a spatial autocorrelation test can be carried out using the moran index test [16] The moran index can be expressed by the following formula [5]:
Hypothesis:
$H_0 : I = 0$ (no spatial autocorrelation occurs)
$H_1 : I \neq 0$ (there is at least one spatial autocorrelation)
Test statistics:

$$Z(I) = \frac{I - E(I)}{\sqrt{var(I)}} \tag{9}$$

with:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) \left(x_j - \bar{x}\right)}{S_0 \left(\sum_{i=1}^{n} (x_i - \bar{x})^2\right)} \tag{10}$$

$$Var(I) = \frac{n^2 S_1 - n^2 S_2 + 3S_0^2}{(n^2 - 1) S_0^2} - [E(I)]^2 \tag{11}$$

$$E(I) = I_0 = -\frac{1}{n - 1} \tag{12}$$

with:
I : Moran's I
n : the number of observations
x_i : value the data to-$i, i = 1,2,3, \dots, n$
x_j : value the data to-$j, j = 1,2,3, \dots, n$
$\bar{x}$: average value of data x_i from the n region
w_{ij} : standardized spatial weighting matrix elements between regions i and j
Rejection decision making H_0 if $|Z_{\text{hitung}}| > Z_{\alpha/2}$ or $p - value < \alpha$.

2.2.5 Spatial Regression Model

Spatial regression is a statistical analysis method used to evaluate the relationship between dependent and independent variables, paying attention to spatial influences and correlations between data. This technique is particularly applied to spatial data, which is data that is influenced by location factors or spatial effects.

According to Anselin, (1988) the basic model for spatial regression can be expressed in the form of the following equations [5].

$$\boldsymbol{y} = \rho \boldsymbol{W_1} \boldsymbol{y} + \boldsymbol{X\beta} + \boldsymbol{u} \tag{13}$$
$$\boldsymbol{u} = \lambda \boldsymbol{W_2} \boldsymbol{u} + \boldsymbol{\varepsilon};\ \varepsilon \sim N(0, \sigma^2 \boldsymbol{I})$$

with:
$\boldsymbol{y}$: dependent variable vector with size $n \times 1$
ρ : spatial lag parameter coefficient of dependent variables
$\boldsymbol{W_1}$: spatial weighting matrix with size $n \times n$
$\boldsymbol{W_2}$: spatial weighting matrix with size $n \times n$
$\boldsymbol{X}$: an independent variable matrix with size $n \times (k + 1)$
$\boldsymbol{\beta}$: regression parameter coefficient vector with size $(k + 1) \times 1$
λ : spatial error parameter coefficient
$\boldsymbol{u}$: error vector containing spatial effects with size $n \times 1$
$\boldsymbol{\varepsilon}$: error vector with size $n \times 1$ normal distributed size with zero mean and variance $(\sigma_\varepsilon^2 I_n)$
$\boldsymbol{I}$: identity matrix with size $n \times n$

2.2.6 *Spatial Durbin Model* (SDM)

This model is a form of spatial modeling carried out through an autoregressive approach. Durbin spatial regression is a development of the Spatial Autoregressive (SAR) model that not only considers spatial lag on dependent variables, but also on independent variables [6] The SDM model is expressed in the following equation [17].

$$\boldsymbol{y} = \rho\boldsymbol{W}\boldsymbol{y} + a\boldsymbol{1_n} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \boldsymbol{\varepsilon} \sim N(0, \sigma^2\boldsymbol{I}) \tag{14}$$

Based on the existing general model of spatial regression, this approach can further be developed into SDM, with the following derivative form:

$$y_i = \rho\sum_{j=1}^{n} w_{ij}y_j + \alpha + \sum_{k=1}^{p} \beta_k x_{ki} + \theta_k \sum_{k=1}^{p}\sum_{j=1}^{n} w_{ij}x_{kj} + \varepsilon_i \tag{15}$$

with:

y_i	:	the value of the dependent variable in the to region-i
y_j	:	the value of the dependent variable in the to region-j
w_{ij}	:	value of the spatial weighter which informs the relationship between the regions to-i with the region to-j
α	:	constant parameters
β_k	:	parameter values without spatial weighting for independent variables with size $(k+1)\times 1$
θ_k	:	value of regression parameters with spatial weights for independent variables with size $(k+1)\times 1$
x_{ki}	:	the value of an independent variable to-k in the region to-i
x_{kj}	:	the value of an independent variable to-k in the region to-j

Equation 14 can be simplified and written into:

$$\boldsymbol{y} = \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{Z}\boldsymbol{\delta} + \boldsymbol{\varepsilon} \tag{16}$$

If for example $\boldsymbol{Z\delta} = a\boldsymbol{1_n} + \boldsymbol{X\beta} + \boldsymbol{WX\theta}$, throw $\boldsymbol{Z} = [\boldsymbol{1_n} \quad \boldsymbol{X} \quad \boldsymbol{WX}]$ dan $\boldsymbol{\delta} = [\boldsymbol{\alpha} \quad \boldsymbol{\beta} \quad \boldsymbol{\theta}]^{\boldsymbol{T}}$.

with:

$\boldsymbol{y}$	:	dependent variable vector with size $n \times 1$
$\boldsymbol{X}$	:	an independent variable matrix with size $n \times (k+1)$
ρ	:	variable spatial lag coefficient
α	:	constant parameters
$\boldsymbol{\delta}$	:	dependent variable parameter vector and independent variable
$\boldsymbol{\beta}$	:	regression parameter vector with size $k \times 1$
$\boldsymbol{\theta}$	:	dimensional independent variable spatial lag parameter vector $p \times 1$
$\boldsymbol{W}$	:	weighting matrix with size $n \times n$
$\boldsymbol{\varepsilon}$	:	vector with size $n \times 1$
$\boldsymbol{1_n}$	:	vector containing the number 1 with the $n \times 1$

2.2.7 Parameter Estimation Spatial Durbin Model (SDM)

Parameter estimation in the SDM model is carried out through the Maximum Likelihood Estimation (MLE) approach. This approach is known for its ability to provide efficient and consistent estimation, making it a top choice in model parameter analysis. In this case, the likelihood function is formed based on the assumption that the error $(\boldsymbol{\varepsilon})$ distributed normally, which is expressed through the following equation [18]:

$$\boldsymbol{y} = \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{Z}\boldsymbol{\delta} + \boldsymbol{\varepsilon} \tag{17}$$

$$\boldsymbol{\varepsilon} = \boldsymbol{y} - \boldsymbol{\rho}\boldsymbol{W}\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{\delta} \tag{18}$$

$$\boldsymbol{\varepsilon} = (\boldsymbol{I_n} - \boldsymbol{\rho}\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{\delta} \tag{19}$$

Opportunity density function of ε_i, namely:

$$f(\varepsilon_i|\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{\varepsilon_i^2}{\sigma^2}} \tag{20}$$

The likelihood function is obtained, namely:

$$\begin{aligned} L(\sigma^2; \varepsilon) &= \prod_{i=1}^{n} f(\varepsilon_i|\sigma^2) \\ &= \left(\frac{1}{2\pi\sigma^2}\right)^{n/2} \exp\left(-\frac{1}{2\sigma^2}(\boldsymbol{\varepsilon}^{\boldsymbol{T}}\boldsymbol{\varepsilon})\right) \end{aligned} \tag{21}$$

By differentiating equation 19 to **y**, obtained the Jacobian function as follows.

$$J = \left|\frac{\partial_\varepsilon}{\partial_y}\right| = \left|\frac{\partial\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)}{\partial_y}\right| = |\boldsymbol{I_n} - \rho\boldsymbol{W}| \tag{22}$$

By adding the Jacobian function to equation 22 and synthesizing equation 20. So the likelihood function is obtained as follows:

$$L(\rho, \boldsymbol{\delta}, \sigma^2|\boldsymbol{y}) = \left(\frac{1}{2\pi\sigma^2}\right)^{n/2} |J| \exp\left(-\frac{1}{2\sigma^2}(\boldsymbol{\varepsilon^T\varepsilon})\right)$$

$$= \left(\frac{1}{2\pi\sigma^2}\right)^{n/2} |\boldsymbol{I_n} - \rho\boldsymbol{W}| \exp\left(-\frac{1}{2\sigma^2}\left(\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)^T\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)\right)\right) \tag{23}$$

Then the function of likelihood in equation 23 in ln-kan becomes as follows.

$$ln(L) = ln\left(\frac{1}{2\pi\sigma^2}\right)^{n/2} |\boldsymbol{I_n} - \rho\boldsymbol{W}| \exp\left(-\frac{1}{2\sigma^2}\left(\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)^T\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)\right)\right)$$

$$= \frac{n}{2} ln(2\pi) - \frac{n}{2}\ln(\sigma^2) + ln|\boldsymbol{I_n} - \rho\boldsymbol{W}| + \left(-\frac{1}{2\sigma^2}\left(\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)^T\left((\boldsymbol{I_n} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z\delta}\right)\right)\right) \tag{24}$$

Determination of estimating parameters ρ, parameters $\boldsymbol{\delta}$**,** parameters σ^2 on the SDM model, obtained by maximizing the function of equation 24 by differentiating the ρ, $\boldsymbol{\delta}$ and σ^2.

$$ln = \left(L(\rho)\right) = C - \frac{n}{2}\ln\left((\boldsymbol{e_0} - \hat{\rho}\boldsymbol{e_1})^T(\boldsymbol{e_0} - \hat{\rho}\boldsymbol{e_1})\right) + \ln|\boldsymbol{I} - \rho\boldsymbol{W}| \tag{25}$$

$$\boldsymbol{\hat{\delta}} = \boldsymbol{\hat{\delta}_0} - \hat{\rho}\boldsymbol{\hat{\delta}_1} \tag{26}$$

$$\hat{\sigma}^2 = \frac{(\boldsymbol{e_0} - \hat{\rho}\boldsymbol{e_1})^T(\boldsymbol{e_0} - \hat{\rho}\boldsymbol{e}_1)}{n} \tag{27}$$

2.2.8 Parameter Significance Test

Significance tests for parameters in the SDM model were performed using wald test statistics [5] The testing process for each parameter in the SDM model can be described as follows:

To test the significance of the parameters ρ, the following hypothesis formulation is used:

$H_0: \rho = 0$

$H_1: \rho \neq 0$

Test statistics are expressed as follows:

$$W_\rho = \frac{\hat{\rho}^2}{var(\hat{\rho})} \sim \chi_1^2 \tag{28}$$

with:

$var(\hat{\rho})$ is the diagonal element of the variance matrix that corresponds to the ρ

Testing criteria:

Reject H_0 if the test statistics $W_\rho > \chi^2_{(\alpha,1)}$

To test the parameters β used the following hypothesis:

$H_0: \beta_j = 0$

$H_1: \beta_j \neq 0, j = 1,2, \dots, \rho$

Test statistics are expressed as follows:

$$W_\beta = \frac{\hat{\beta_j}^2}{var(\hat{\beta}_j)} \sim \chi_1^2 \tag{29}$$

with:

$var(\hat{\beta}_j)$ is the diagonal element of the variance matrix that corresponds to the β

Testing criteria:

Reject H_0 if the test statistics $W_\beta > \chi^2_{(\alpha,1)}$

To test the parameters θ used the following hypothesis:

$H_0: \theta_j = 0$

$H_1: \theta_j \neq 0, j = 1,2, \dots, \rho$

Test statistics are expressed as follows:

$$W_\theta = \frac{\widehat{\theta_j}^2}{var(\widehat{\theta_j})} \sim \chi_1^2 \tag{30}$$

with:

$var(\widehat{\theta_j})$ is the diagonal element of the variance matrix that corresponds to the θ

Testing criteria:

Reject H_0 if the test statistics $W_\theta > \chi^2_{(\alpha,1)}$

2.2.9 Best Model Selection

The selection of the best model is carried out to produce a viable model in the SDM test can be seen from the value of the determination coefficient (R^2) and the value of Akaike's information Criterion (AIC).

2.2.9.1 Koefisien Determinasi (R^2)

Coefficient of determination (R^2) serves to assess the extent to which the model can explain the variations that occur in dependent variables. Value R^2 ranges from zero to one. When the value of R^2 close to zero, this indicates that explanatory variables have a very limited ability to explain variations in dependent variables. Conversely, if the value R^2 approaching one, this shows that the model has an excellent ability to explain the variations that exist. Thus, a model that has a value R^2 larger is generally considered better [19] The coefficient of determination can be calculated using the following formula:

$$R^2 = 1 - \frac{SSE}{SST} \tag{31}$$

with:
SSE : residual square
SST : total squares

2.2.9.2 *Akaike's Information Criterion* (AIC)

Akaike's Information Criterion (AIC) serves to evaluate the extent to which the model fits with existing data. A model is considered good if it has the lowest AIC value. The formula for calculating AIC in the context of model research can be stated as follows [20].

$$AIC = -2\ln L(\beta) + 2k \tag{32}$$

with:
$Ln(L(\beta))$: the likelihood value of the model
k : number of parameters/ free degrees in the model

3. Results and Discussion

3.1 Descriptive Analysis of Research

Before the main analysis is carried out, descriptive analysis and mapping are first carried out to understand more deeply the characteristics of each variable and its distribution in each region. The results of the descriptive analysis will generally be displayed in the form of a table to facilitate interpretation and understanding of the data used.

Table 3. Descriptive Statistical Analysis

Statistics Descriptive				
Variable	**Minimum**	**Maximum**	**Mean**	**Std. Deviasi**
$\boldsymbol{Y}$	5.13	27.95	19.3964	5.99823
$\boldsymbol{X_1}$	1.95	5.00	3.7200	0.88445
$\boldsymbol{X_2}$	8.48	12.24	9.7173	1.02388
$\boldsymbol{X_3}$	60.80	72.51	66.5445	4.40879
$\boldsymbol{X_4}$	4.16	22.66	9.0918	6.13198

Table 3 presents the results of the descriptive analysis for each variable, which includes the minimum, maximum, mean, and standard deviation values. For example, in variable Y, which is the percentage of poor people, it is known that the minimum value is found in Ambon City of 5.13. This shows that Ambon City has the lowest percentage of poor people in Maluku Province. Meanwhile, the maximum value is found in Southwest Maluku Regency at 27.95, which means that this area has the highest percentage of poor people. The average value or mean of the percentage of poor people in all districts/cities in Maluku Province is 19.3694, which describes the average percentage of poor people in Maluku Province.

Similar descriptive analysis was also performed for other variables. To clarify the differences between regions, each variable is classified into three categories, namely high, medium, and low. The results of this classification are then visualized in the form of thematic maps with color variations based on these categories. Spatial visualization of each variable for all 11 regencies/cities in Maluku Province was made using the output of Geoda software.

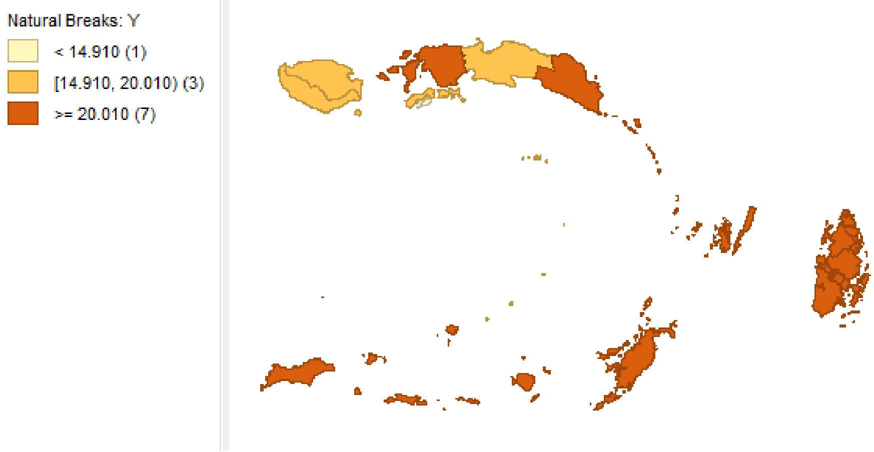

Fig. 4. Map of Maluku Province by Percentage of Poor Population

Based on the thematic map in Fig. 4, it is known that the pattern of distribution of the percentage of poor people in the Maluku region is divided into three color categories, which indicate the low, medium and high percentage of poor people in each region. The first category shows that the area has the lowest percentage of confirmed poor population, which is less than 14.910%. The only area that falls into this category is Ambon City. Furthermore, the second category indicates areas with a moderate poverty percentage, in the range of 14.910% to 20.010%. Some of the areas included in this category include Central Maluku, Buru and South Buru Regencies. Finally, the third category describes areas with a high percentage of poor population, namely with a confirmed number of 20.010% or more. Areas that fall into this category include West Seram Regency, Eastern Seram Regency, Aru Islands, Tanimbar Islands, Southwest Maluku, Southeast Maluku, and Tual City.

3.2 Multiple Regression Linear

Multiple linear regression modeling was performed to find out the factors that affect poverty. Testing on multiple linear regression by estimating parameters using the Ordinary Least Square (OLS) method. The following is an estimate of multiple linear regression parameters.

Table 4. Multiple Linear Regression Parameter Estimation

Parameter	Estimation	$\lvert t_{count} \rvert$	*p-value*
$\boldsymbol{\beta_0}$	118.7512	3.617	0.0111
$\boldsymbol{\beta_1}$	4.4940	2.299	0.0612
$\boldsymbol{\beta_2}$	-5.6056	-2.973	0.0249
$\boldsymbol{\beta_3}$	-0.8909	-2.443	0.0502
$\boldsymbol{\beta_4}$	-0.2549	-1.034	0.3410

Based on Table 4, it can be seen that the results of parameter estimation have one independent variable that has a *p-value* that is smaller than the significant leveli $\alpha = 0.05$ that is the variable of the average length of school (X_2). So it can be concluded that the variable of average length of school has a significant effect on the variable of the percentage of the poor population. Meanwhile, the variable growth rate of gross regional domestic product per capita (X_1), labor force participation rate (X_3) and percentage of the population (X_4) has a *p-value* greater than the significance level $\alpha = 0.05$ This means that these variables do not have a significant effect on the variable percentage of the poor population. From the results of parameter estimation, the multiple linear regression model formed is as follows:

$$\hat{Y} = 118.7512 + 4.4940X_1 - 5.6056X_2 - 0.8909X_3 - 0.2549X_4$$

3.3 Regression Model Assumptions

In the classical assumption test, there are four main assumptions that must be met in order for a data to be modeled linearly properly.

3.3.1 Normality Test

The Shapiro-wilk test is used to test the assumption of residual normality. The table below shows the results of the Shapiro-wilk Test.

Table 5. Shapiro-wilk Test Results

W	***p-value***
0.9499	0.6432

Based on Table 5, it is known that the p-value is 0.6432. When compared to the significance level $\alpha = 0.05$, then a p-value greater than the alpha value indicates that there is not enough evidence to reject H_0. Thus, it can be concluded that the residual in this model follows the normal distribution.

3.3.2 Heteroskedasticity Test

The heteroscedasticity test in this study was carried out using the Breusch-Pagan test, which aims to assess whether there is a residual variance disparity in each observation. The following are the results of the heteroscedasticity test with the Breusch-Pagan test.

Table 6. Breusch-Pagan Test Results

Breusch-Pagan	$\chi^2_{(0,05:4)}$	***p-value***
1.2162	9.488	0.8754

Based on the results in Table 6 the Breusch-Pagan value of 1.2162 is smaller than the table value and $\chi^2_{(0,05:4)} = 9.488$ $p\text{-}value = 0.8754 > \alpha = 0.05$, so the decision taken is to accept H_0. Thus, it can be concluded that the data does not experience heteroscedasticity.

3.3.3 Multicollinearity Test

To determine whether there is a linear relationship or correlation between independent variables in the regression model, multicollinearity detection is used. In accordance with Equation 4, the multicollinearity test is performed by calculating the Variance Inflation Factor (VIF). The following are presented the results of the multicollinearity test based on the VIF value obtained.

Table 7. Variance Inflation Factor (VIF) Test

Variable	**Nilai VIF**
X_1	1.864742
X_2	2.324907
X_3	1.611937
X_4	1.424971

Based on the results in Table 7, it can be seen that all the variables tested obtained a VIF value of less than 10, thus indicating that there are no symptoms of multicollinearity or no correlation between independent variables.

3.3.4 Autocorrelation Test

Autocorrelation was tested using the Durbin-Watson (DW) method. The following results of the non-autocorrelation assumption test are presented in the form of a table.

Table 8. Durbin-Watson (DW) Test Results

DW	***p-value***
2.4261	0.7238

Based on Table 8, the calculation results carried out using the R application show that the value is 2.4261, with DW *p-value* by 0.7238. Refer to Table 2.1, which contains the lower limit value (d_L) and upper limit (d_U) at a significance level of 5% with the number of independent variables k as many as 5 and the number of observationsi n a total of 11, obtained a score of $d_L = 0.3155$ and $d_U = 2.6446$ as stated in appendix 14. Based on the decision-making criteria, if the value DW be in range $4 - d_U < d < 4 - d_L$, that is $1.3554 < 2.4261 < 3.6845$. then the regression model can be stated to be undecided. This condition requires further testing so that it can be known to be non-autocorrelated by using the Run Test.

Run Test is carried out to determine the existence of continuous patterns or sequences in data that are sequenced and obtained a *p-value* of 0.5023, because the value of *p-value* greater than α, so it can be concluded that there is no autocorrelation.

3.4 Spatial Weighting Matrix

In this study, a spatial weighting matrix was prepared for the Maluku region. The type of boundary crossing used is Queen Contiguity, which refers to the interaction between the sides and corners of the territory. The process of compiling this matrix involves paying attention to regional boundaries, such as Buru Regency which is directly adjacent to South Buru Regency. Each adjacent area is given a weight of 1, while the unbordered area is given a weight of 0. The same approach is applied to other regions.

Furthermore, the relationship between districts/cities in Maluku Province is arranged in a spatial weighting matrix that is still not standardized, with the size of the matrix covering 11 regions in rows and columns.Neighboring territories are considered to have similar or equal influence. Therefore, standardization is carried out proportionally, namely by giving equal weight to each area that borders one specific area. The standardization process is done by dividing each element in the matrix by the number of neighbors per row.

$$W = \begin{bmatrix} 0 & 0 & 0 & 0 & 0{,}333 & 0{,}333 & 0 & 0 & 0 & 0{,}333 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

3.5 Spatial Autocorrelation Test

Before developing a spatial regression model, spatial effects were evaluated by performing spatial autocorrelations using the Moran Index. According to Equation 9, the results of the moran index test can be seen in the following table.

Table 9. Moran Index Value

Variable	I	*p-value*
Y	0.14488	0.0494
X_1	0.06695	0.2366
X_2	0.18011	0.0032
X_3	0.34721	0.1175
X_4	0.55406	0.0055

Based on Table 9, it is obtained that all variables Y, X_2, X_4 has a *p-value* $< \alpha = 0.05$, which means H_0 rejected. This shows that there is a spatial autocorrelation between locations in dependent and independent variables.

3.6 Parameter Estimation Spatial Durbin Model (SDM)

After the spatial effect test was carried out, it was found that there were spatial dependencies on independent and dependent variables based on the results of the autocorrelation test using the moran index, then an SDM modeling analysis was carried out. To estimate the parameters in the model, the MLE method is used. The table below presents the results of the parameter estimation.

Table 10. Estimation Spatial Durbin Model

Parameter	Estimated Value
β_0	12.62855
β_1	-2.11156
β_2	-2.59860
β_3	0.73263
β_4	-0.56066
θ_1	17.85220
θ_2	6.71989
θ_3	-1.71923
θ_4	-1.29979
ρ	1.6408×10^{-8}

3.7 Parameter Significance Test

The parameter significance test in the SDM model was partially carried out to determine the variables that had a significant influence on the poverty model formed. This test uses the Wald test method. The table below presents the results of the calculation of the Wald value for each parameter.

Table 11. Wald Value

Parameter	$Wald$	Verdict H_0
β_0	0.4237924	Fail to reject H_0
β_1	2.734995	Fail to reject H_0
β_2	7.173304	Rejected H_0
β_3	7.776343	Rejected H_0
β_4	3.235911	Fail to reject H_0
θ_1	12.97659	Rejected H_0
θ_2	7.039662	Rejected H_0
θ_3	18.40845	Rejected H_0
θ_4	7.818023	Rejected H_0
ρ	$2.5128606 \times 10^{-15}$	Fail to reject H_0

Based on Table 11 which shows that the Wald value at the parameters $\beta_2, \beta_3, \theta_1, \theta_2, \theta_3\ dan\ \theta_4 > \chi^2_{0,05;1} = 3.841$. So it is concluded that minus H_0 means that there is at least one independent variable that has a significant effect on the dependent variable.

3.8 Model *Spatial Durbin Model* (SDM)

Based on Table 10, the SDM model formed is as follows:

$$y_i = 1.6408 \times 10^{-8} \sum_{j=1}^{n} w_{ij} y_j + 12.62855 - 2.11156 x_1 - 2.59860 x_2 + 0.73263 x_3 - 0.56066 x_4 + 17.85220 \sum_{j=1}^{n} w_{ij} x_{1j} + 6.71989 \sum_{j=1}^{n} w_{ij} x_{2j} - 1.71923 \sum_{j=1}^{n} w_{ij} x_{3j} - 1.29979 \sum_{j=1}^{n} w_{ij} x_{4j}$$

Based on the results of the spatial model estimation, it is known that the estimated value (ρ) of 1.6408×10^{-8} which is positive indicates that a one percent increase in poverty in neighboring areas will result in an increase in poverty of 1.6408×10^{-8} percent in the region itself. The parameter value (β_1) of -2.11156 which is negative indicates that for every one percent increase in the growth rate of GRDP per capita (X_1) in the region itself, there will be a decrease in poverty of 2.11156 percent in the region assuming other variables are constant. The parameter value $(\beta_2)$of -2.59860 which is negative indicates that for every one unit increase in the average length of schooling (X_2) in the region itself, there will be a decrease in poverty of 2.59860 percent in the region assuming other variables are constant. The positive value of parameter (β_3)

of 0.73263 indicates that for every one percent increase in the labor force participation rate (X_3) in one's own region, poverty increases by 0.73263 percent, assuming other variables remain constant. The negative value of parameter (β_4) of -0.56066 indicates that for every one percent increase in the population (X_4) in one's own region, poverty decreases by 0.56066 percent, assuming other variables remain constant.

The positive value of parameter (θ_1) of 17.8522 indicates that for a one percent increase in the per capita GRDP growth rate in neighboring regions, poverty increases by 17.8522 percent in one's own region. The positive value of parameter (θ_2) of 6.71989 indicates that for a one-unit increase in the average length of schooling in neighboring regions, poverty increases by 6.71989 percent in one's own region. Parameter (θ_3) of -1.71923 with a negative value indicates that a one percent increase in the labor force participation rate in neighboring areas results in a 1.71923 percent decrease in poverty in the region itself. Parameter (θ_4) of -1.29979 with a significant negative value indicates that a one percent increase in the population in neighboring areas results in a 1.29979 percent decrease in poverty in the region itself.

3.9 Best Model Selection

Two commonly used indicators to evaluate and compare model quality are R^2 and AIC. Next, the following table presents a comparison of the values R^2 and AIC between the SDM model and the multiple linear regression model.

Table 12. Values R^2 and AIC of Each Model

Model	AIC	R^2
OLS	67.0699	0.5544
SDM	54.831	0.9646

Based on Table 12 shows the value of R^2 and the AIC values on each model are displayed. The test results showed that the AIC value in the SDM model was smaller than the AIC value in the multiple linear regression model. While the value of R^2 in the SDM model is also higher than the value of R^2 in multiple linear regression models. Therefore, it can be concluded that the SDM model is better than the multiple linear regression model to model the factors that affect poverty in Maluku Province in 2024.

4. Conclusion

Based on the results and discussion, it can be concluded that:

1. The form of the SDM regression model, which is formed between dependent and independent variables, is as follows.

$$\begin{aligned} y_i = {} & 1.6408 \times 10^{-8} \sum_{j=1}^{n} w_{ij} y_j + 12.62855 - 2.11156 x_1 - 2.59860 x_2 + 0.73263 x_3 - 0.56066 x_4 \\ & + 17.85220 \sum_{j=1}^{n} w_{ij} x_{1j} + 6.71989 \sum_{j=1}^{n} w_{ij} x_{2j} - 1.71923 \sum_{j=1}^{n} w_{ij} x_{3j} \\ & - 1.29979 \sum_{j=1}^{n} w_{ij} x_{4j} \end{aligned}$$

2. The factors that affect poverty in Maluku Province significantly consist of direct and indirect influences, namely:

a. Directly, the variables of average school age and labor force participation have a significant effect on poverty.

b. Indirectly, variables of GRDP growth rate per capita, average length of schooling, labor force participation rate and percentage of population in neighboring areas have a significant effect on poverty in a region, which shows a spillover effect between regions.

Acknowledgment

Thank you to all parties who have helped in the research process and creation of this article.

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