Available online at https://ejournal.corespub.com/index.php/ijmsc/index

International Journal of Mathematics, Statistics, and Computing

e-ISSN 3025-0803

Vol. 1, No. 3, pp. 35-43, 2023

Modeling Life Expectation of Population in Sumatra Island Using Durbin Spatial Model Analysis

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Abstract

Life expectancy is an indicator in measuring government performance in improving the level of health and well-being of the population of a region. While life expectancy on Sumatra Island has variable values, the quality of public health is less uniform. These variations can be caused by several factors such as education, health services, and economic conditions. Therefore, the government needs to provide further treatment on Sumatra Island by identifying factors that affect life expectancy. The study used a Spatial Durbin Model with Queen Contiguity and Rook Contiguity 154 districts/cities on the island of Sumatra. The variables used in the study were data on life expectancy, average school age, the percentage of many infants who received complete immunization, the percent of households having access to decent drinking water, the proportion of the poor population, the regional gross domestic product in 2021. The results of the study showed that the best model was the model that used the Queen Contiguity weighing matrix because it had a smaller AIC value of 365.22. Factors influencing the life expectancy of the population of Sumatra Island in 2021 using the durbin spatial model with the Queen weigher are the average age of school, the percentage of the poor population, and the regional gross domestic product.

Keywords: Life expectancy, queen contiguity, rook contiguity, spatial durbin model

1. Introduction

Life expectancy is an indicator in measuring government performance in improving the health and welfare of the population of a region. Life expectancy can be defined as the number of years expected to live for a certain person or group of people (Vachon & Sestier, 2013). The island of Sumatra is ranked second based on the highest population density after Java Island with a population distribution percentage of 21.7% in 2021 (Ministry of Health RI, 2022).

Based on information obtained from the Central Statistics Agency (2021a), the average life expectancy on the island of Sumatra in 2021 is 70.25 years. The average life expectancy on the island of Sumatra also shows a position below the life expectancy in Indonesia, which is 73.5 years. This shows that the government needs to give further attention and management both in terms of health services, the environment, and the social economy of the population on the island of Sumatra which have not been realized optimally.

Life expectancy in Indonesia has varying values, meaning that the quality of public health in Indonesia is uneven. Variations in life expectancy can be caused by several factors such as education, health services, and economic conditions (Anggraini & Lisyaningsih, 2013). The increase or decrease in life expectancy cannot be separated from many influencing factors. Analysis of the factors that affect life expectancy can be done using spatial regression analysis.

Spatial regression is an analysis used to determine the relationship between the independent variable and the dependent variable by taking into account the influence of location linkages (Delvia et al., 2021). The spatial regression method that can be used if the data has a spatial relationship to the response variable is the autoregressive spatial model. Meanwhile, if the data has a spatial relationship to the response variables and explanatory variables, the model that can be used is the Durbin spatial model.

Previous research using the durbin spatial model analysis was conducted in China by Wang et al (2021), discussing the spatial impact of green technology innovation on total green factor productivity. It was found that green technology innovation has a significant positive effect on total green factor productivity alone and has a negative effect on surrounding area during the observation period. Subsequent research, discussing the topic of life expectancy, was carried out by Pratiwi & Budyanra (2020) using the panel data regression method with the aim of knowing the analysis of variables that have a significant influence on life expectancy in Maluku Province, obtained variables that have a significant influence, namely variables GRDP per capita, household access to clean water and the ratio of puskesmas per district.

In this study, the data used is data for 2021 from 154 Regencies/Cities on Sumatra Island. The purpose of this study was to identify the factors that influence the life expectancy of the population of districts/cities on the island of Sumatra and find out how well the model is formed in explaining life expectancy on the island of Sumatra.

2. Materials and Methods

2.1. Materials

This study uses secondary data obtained from the publication of the Central Bureau of Statistics (BPS). The data used is data that affects 154 Regencies/Cities on Sumatra Island in 2021. The variables used are Life Expectancy, Average Length of Schooling, Percentage of Households Having Access to Adequate Drinking Water, Percentage of Many Toddlers Who Receive Complete Immunization , Percentage of Poor Population, and GRDP at Current Prices.

2.2. Methods

Spatial regression is an analysis that assesses the relationship between one variable and another that has a spatial effect on the location where the observation is made (Fatati et al., 2017). Tests in analyzing spatial effects are based on the spatial weighting matrix used to determine the closeness of the relationship between observations (Anselin, 1988). The form of the general model of spatial regression can be written as follows:

$$\hat{\boldsymbol{y}} = \rho\boldsymbol{Wy} + \boldsymbol{X\beta} + \lambda\boldsymbol{Wu} + \boldsymbol{\varepsilon},\ \ \boldsymbol{\varepsilon} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{I\sigma^2}) \tag{1}$$

The spatial weighting matrix is a matrix that describes the interrelationships between regions and is obtained based on distance or neighbor information. Basically, the weight of the distance between a location and the surrounding locations is determined by the distance between the two areas (Ariesta et al., 2022). The form of the spatial weighting matrix is obtained in equation (2) as follows:

$$\boldsymbol{W} = \begin{pmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{11} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{pmatrix} \tag{2}$$

with

$$W_{ij} = \begin{cases} 0, & \text{if } i \text{ and } j \text{ not neighbors or } i = j \\ 1, & \text{for neighbors} \end{cases}$$

According to LeSage and Pace (2009), there are several methods for determining neighborhood relationships between locations as follows:

1. Rook Contiguity

Rook Contiguity or side intersection is defined as $W_{ij} = 1$ for the area adjacent to the observed area, $W_{ij} = 0$ for other areas. It can be presented in Figure 1, that regions B1, B2, B3 and B4 are neighbors of region A.

	Region B2	
Region B1	Region A	Region B3
	Region B4	

Figure 1: Rook Contiguity

2. Bishop Contiguity

Bishop Contiguity or corner intersection is defined as $W_{ij} = 1$ for the corner point area with the observed corner area, $W_{ij} = 0$ for other areas. It can be presented in Figure 2, that regions C1, C2, C3, and C4 are neighbors of region A.

Region C1		Region C2
	Region A	
Region C4		Region C3

Figure 2: Bishop Contiguity

Spatial analysis needs to be carried out spatial effect tests to describe situations where observations in an area depend on neighboring observations in the nearest location (LeSage & Pace, 2009). The spatial effect test can be divided into two aspects in the spatial regression model, namely spatial heterogeneity and spatial dependency. Spatial heterogeneity test is an effect that can indicate the existence of variation between locations. The spatial heterogeneity test was carried out using the Breusch-Pagan (BP) test as follows (Anselin, 1988):

Hypothesis:

$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (There is no spatial heterogeneity)
H_1 : At least there is one $\sigma_1^2 \neq \sigma_2^2$, with $i, j = 1,2, \ldots, n$ (There is spatial heterogeneity)

Test Statistics:

$$Breusch - Pagan = \frac{1}{2}\boldsymbol{f^T Z}(\boldsymbol{Z^T Z})^{-\mathbf{1}}\boldsymbol{Z^T f} \tag{3}$$

$\boldsymbol{Z}$ represents an $n \times (p+1)$ matrix containing standardized vectors for each observation, $\boldsymbol{T}$ represents the transpose, where $\boldsymbol{f^T} = (f_1, f_2, \ldots, f_n)^{\boldsymbol{T}}$. The test criteria used are if $reusch - Pagan \leq X^2_{(\alpha,p)}$ then H_0 is accepted and if $Breusch - Pagan > X^2_{(\alpha,p)}$ then H_0 is rejected if $Breusch - Pagan > X^2_{(\alpha,p)}$.

The spatial effect test is a test used to determine the spatial interaction in the model (Elhorst, 2014). Spatial effect testing can be done using the Lagrange Multiplier (LM) test. The hypothesis used in the Lagrange Multiplier test is as follows:
$H_0 : \rho = 0$ (There is no spatial effect)
$H_1 : \rho \neq 0$ (There is a spatial effect)
Test Statistics:

$$LM_\rho = \frac{\left[e^T(\boldsymbol{I}_T \otimes \boldsymbol{W})\dfrac{\boldsymbol{y}}{\hat{\sigma}_e^2}\right]^2}{J} \tag{4}$$

e represents the error vector of the combined regression model, $\boldsymbol{I}_T$ represents the identity matrix $\times T$, T represents the number of time periods, $\otimes$ represents the product kronecker, $\hat{\sigma}_e^2$ represents the estimated error of the combined regression model, J represents the jacobian function. The test criteria used are if $LM \leq X^2_{(\alpha,1)}$ then H_0 is accepted and if $LM > X^2_{(\alpha,1)}$ then H_0 is rejected.

Spatial autocorrelation test is a test used to determine the correlation between variables with themselves based on space. Spatial autocorrelation testing can be done using the Moran Index test. In general, the Moran Index value is determined by the following formula (Anselin, 1988):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{5}$$

I represents Moran's Index, x_i represents the observed value at location $i = 1,2, \ldots, n$, x_j represents the observed value at location $j = 1,2, \ldots, n$, $\bar{x}$ represents the average value of the observed values.

The range of Moran's Index values with the spatial weighting matrix ranges from $-1 < I < 1$. If the Moran Index value is $-1 < I < 0$, it means that there is negative spatial autocorrelation, if the value is $0 < I < 1$, it means that there is positive spatial autocorrelation and if the value is 0, it means that there is no spatial autocorrelation (Habinuddin, 2021). Moran's index needs to be tested for significance with the hypothesis used as follows:
$H_0 : I = 0$ (There is no spatial autocorrelation)
$H_1 : I \neq 0$ (There is spatial autocorrelation)

Test Statistic:

$$Z(I) = \frac{I - E[I]}{\sqrt{Var(I)}} \tag{6}$$

where $E[I]$ is the expected value of the Moran Index as follows:

$$E[I] = \frac{-1}{n-1} \tag{7}$$

and $Var(I)$ express the variance of Moran's Index with the following formula:

$$Var(I) = \frac{n^2 S_1 - nS_2 + 3S_0^2}{S_0^2(n^2 - 1)} - (E[I])^2 \tag{8}$$

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \tag{9}$$

$$S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(W_{ij} + W_{ji})^2 \tag{10}$$

$$S_2 = \sum_{i=1}^{n}\left(\sum_{i=1}^{n} W_{ij} + \sum_{j=1}^{n} W_{ji}\right)^2 \tag{11}$$

The test criteria used is if the value $|Z(I)| \leq Z_{\alpha/2}$ then H_0 received and if value $|Z(I)| > Z_{\alpha/2}$ then H_0 rejected.

In interpreting the Moran Index, you can use the Moran Scatterplot. The Moran Scatterplot is a diagram that shows the relationship between the observed values at a location that is standardized with the average observed values of its neighbors. In the Moran Scatterplot graph, the horizontal axis represents the standardized value of observations and the vertical axis represents the standardized average neighbor value. The Moran Scatterplot can be shown in Figure 4 as follows:

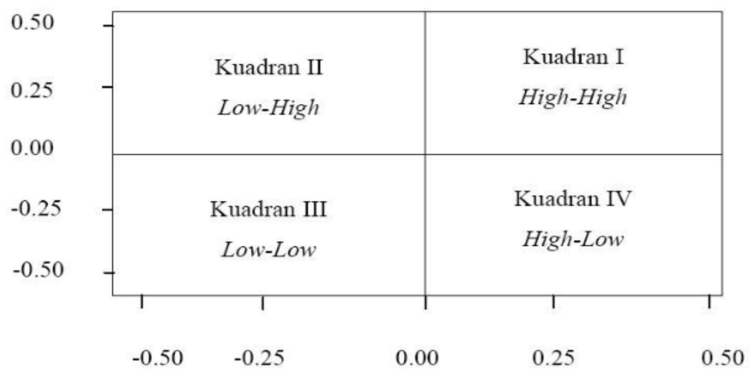

Figure 4: Moran Scatterplot

In the picture Moran Scatterplot has four different quadrants showing four types of spatial relationships between an area and adjacent areas as follows:

1. Quadrant I (High-High), defines areas with high observation values surrounded by areas with high observation values.
2. Quadrant II (Low-High), defines areas with low observation values surrounded by areas with high observation values.
3. Quadrant III (Low-low), defines areas with low observation values surrounded by areas with low observation values.
4. Quadrant IV (High-Low), defines areas with high observation values surrounded by areas with low observation values.

The Durbin Spatial Model is a spatial modeling with an area approach that has a spatial lag effect on the dependent variable and the independent variable (Wang et al., 2021). Mathematically, the form of the general Spatial Durbin model can be written as follows (Anselin, 1988):

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\alpha} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon} \tag{12}$$

To facilitate the calculation of equation (12) can be written as follows:

$$\boldsymbol{Y} = \boldsymbol{\rho}\boldsymbol{W}\boldsymbol{Y} + \boldsymbol{Z}\boldsymbol{\delta} + \boldsymbol{\varepsilon} \tag{13}$$

$\boldsymbol{Z}$ represents a matrix of size $[n \times (2k+1]$ with $\boldsymbol{Z} = [\boldsymbol{A} \quad \boldsymbol{X} \quad \boldsymbol{WX}]$, $\boldsymbol{\delta}$ represents a vector of size $(2k+1) \times 1$ with $\boldsymbol{\delta} = [\boldsymbol{\alpha} \quad \boldsymbol{\beta} \quad \boldsymbol{\theta}]^{\boldsymbol{T}}$.

Selection of the best model can be done using Akaike's Information Criterion (AIC). The best model can be determined using the smallest AIC value. The AIC value can be calculated as follows (Brooks, 1989):

$$AIC = -2\log(L(\hat{\theta}|y) + 2\beta \qquad ($$

$L(\hat{\theta}|y)$ states the likelihood function of the estimated parameter, β specify the parameters to be estimated.

Life expectancy is an estimate of the average length of life from birth that an individual will achieve. Life expectancy can also describe the level of success of programs in the health sector in a region (Amalia & Mahmudah, 2019). Factors that affect life expectancy include:

1. Average length of schooling
   The average length of school is an indicator of education which explains that the higher the average length of school. Kabir (2008) says that education is considered a factor that influences life expectancy. Education can increase labor productivity, population growth, social welfare and increase population awareness of health in increasing life expectancy.
2. Percentage of children under five who received complete immunization
   Immunization is an effort to actively increase a person's immunity against a disease so that if one day they are exposed to the disease they will not get sick or only experience a mild illness. The importance of complete

immunization can prevent transmission of certain diseases and can reduce mortality and morbidity in toddlers (Nursery & Chrismilasari, 2019).

3. Percentage of households that have access to proper drinking water
   Drinking water is water that has gone through a processing process or without processing that meets health requirements and can be drunk directly. The lack of even distribution of proper drinking water can affect the development of water-borne diseases in such a way that it can affect the health of the population (Priambodo & Nurhasana, 2020).
4. Percentage of poor population
   The Central Statistics Agency (2021b) says that residents are categorized as poor if they have an average monthly per capita expenditure below the poverty line. The poverty line is the rupiah value that must be spent to meet life needs, both food and non-food minimum living needs. The percentage of poor people can be obtained from the number of poor people divided by the total number multiplied by 100. An increase in the percentage of poor people can reduce the attainment of health scores, especially the life expectancy of an individual (Azahari, 2020).
5. Gross Regional Domestic Product (GDP) at current prices
   GRDP is a factor that can affect life expectancy. Increasing income is important to increase health spending so that the national life expectancy target is achieved. The more GRDP increases, life expectancy will also increase and can reduce infant mortality (Felangi & Yasa, 2021).

3. Results and Discussion

This study uses life expectancy data for districts/cities on Sumatra Island in 2021. Sumatra Island consists of ten provinces, namely Nanggroe Aceh Darussalam, North Sumatra, South Sumatra, West Sumatra, Bengkulu, Riau, Riau Islands, Jambi, Lampung, and Bangka Belitung. Before conducting the analysis, we will explore data on life expectancy in the districts/cities of Sumatra Island in 2021, which can be seen in Figure 5 as follows:

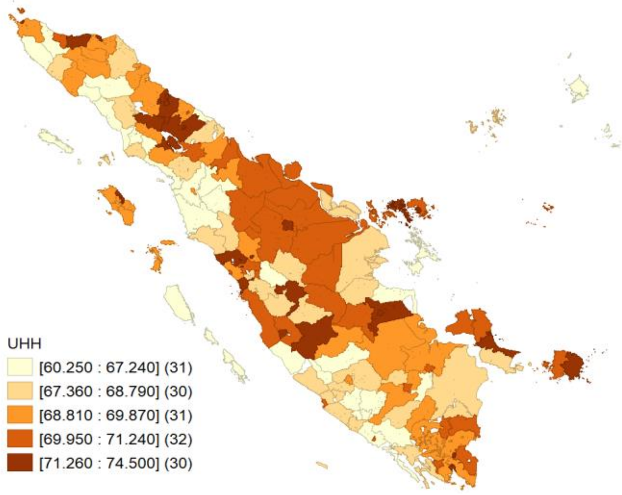

Figure 5: Map of the distribution of life expectancy on the island of Sumatra

Figure 5 shows that there are 31 districts/cities that have the lowest life expectancy and 30 districts/cities that have the highest life expectancy. The lowest life expectancy value is in Sibolga City, which is 60.25 and the highest value is in Bukittinggi, which is 74.50.

Before doing the modeling, first form a weighting matrix Queen Contiguity and Rook Contiguity. Queen Contiguity spatial weighting matrix is a weighting matrix that uses the concept of intersection between corner points and sides of a region with other regions. The form of the Queen Contiguity weighting matrix of 154 Regencies/Cities on Sumatra Island is presented as follows:

$$W_{Queen} = \begin{bmatrix} 0 & \cdots & 0 & 0.25 & 0 & 0 & 0 & 0.25 & \cdots & 0 \\ 0 & \cdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & \cdots & 0 \\ 0.33 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0.20 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0.14 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{14}$$

The Rook Contiguity weighting matrix is a weighting matrix that uses the concept of area's intersection with other regions. The results of the weighting matrix of 154 Regencies/Cities on Sumatra Island based on Rook Contiguity are presented as follows:

$$W_{Rook} = \begin{bmatrix} 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0.25 & \cdots & 0 \\ 0 & \cdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0 & 0.33 & 0.33 & 0 & \cdots & 0 \\ 0.33 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 0.25 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0.14 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \tag{15}$$

Furthermore, to see the spatial diversity between locations, the Breusch-Pagan test was carried out. The results of the Breusch-Pagan test on the life expectancy of districts/cities on Sumatra Island can be presented as follows:

Table 1: Breusch-Pagan Test Results

Weighting Matrix	*BP Test Statistics*	*Df*	*p-value*	Decision	Conclusion
Queen	8.63	10	0.567	H_0 accepted	There is no spatial heterogeneity
Rook	8.45	10	0.585	H_0 accepted	There is no spatial heterogeneity

Based on the Breusch-Pagan test which was carried out with a significance level of $\alpha = 0.05$ using the Queen Contiguity weighting it was obtained $(8.63 < 18.307)$. While the Breusch-Pagan test using Rook Contiguity weights was obtained $(8.45 < 18.307)$. From the results of this decision it can be said that H_0 is accepted, which means that there is no spatial heterogeneity.

Next, do a spatial effect test to test the spatial interaction in the model. The results of the Lagrange Multiplier test on the life expectancy of districts/cities on Sumatra Island can be presented as follows:

Table 2: Lagrange Multiplier Test Results

Weighting Matrix	*Lagrange Multiplier*	*p-value*	Decision	Conclusion
Queen	18.807	1.466×10^{-5}	H_0 rejected	There is a spatial effect
Rook	18.393	1.797×10^{-5}	H_0 rejected	There is a spatial effect

Based on the Lagrange Multiplier test which was carried out with a significance level of $\alpha = 0.05$ using the Queen Contiguity weighting it was obtained $(18.807 > 3.814)$. While the Lagrange Multiplier test was carried out using the Rook Contiguity weighting obtained $(18.393 > 3.814)$. From the results of this decision it can be said that H_0 is rejected, which means that there is a spatial effect on the dependent variable.

The next step is to test the autocorrelation using the Moran Index test. Moran's Index Test is used to determine the correlation between variables with themselves based on space. The results of the Moran Index test with Queen Contiguity weighting at life expectancy are presented as follows:

Table 3: Results of the Moran Index Test with Queen Contiguity weights

Variable	$Z(I)$	I	Decision	Conclusion
Y	5.3707	0.32894	H_0 rejected	There is spatial heterogeneity
X_1	4.3952	0.2690	H_0 rejected	There is spatial heterogeneity
X_2	5.5412	0.3387	H_0 rejected	There is spatial autocorrelation
X_3	8.9759	0.5572	H_0 rejected	There is spatial autocorrelation
X_4	9.1931	0.5686	H_0 rejected	There is spatial autocorrelation
X_5	5.9571	0.3446	H_0 rejected	There is spatial autocorrelation

Rest	5.0406	0.3062	H_0 rejected	There is spatial autocorrelation

Based on the Moran Index test using a significance level of $\alpha = 0.05$, the value $Z_{\alpha/2} = Z_{0.025} = 1.96$ is obtained. In the Moran Index test using Queen weighting, the (I) value for each independent variable and the dependent variable has a value greater than $Z_{\alpha/2} = 1.96$. From the results of this decision it can be said that H_0 is rejected, which means that there is a spatial autocorrelation for each independent variable and the dependent variable with Moran's Index value in the range $0 \leq I < 1$ indicating a positive spatial autocorrelation. Furthermore, the results of the Moran Index test with Rook Contiguity weighting at life expectancy are presented as follows:

Table 4: Results of the Moran Index Test with Rook Contiguity weights

Variable	$Z(I)$	I	Decision	Conclusion
Y	5.3318	0.3277	H_0 rejected	There is spatial autocorrelation
X_1	4.4188	0.2711	H_0 rejected	There is spatial autocorrelation
X_2	5.6051	0.3440	H_0 rejected	There is spatial autocorrelation
X_3	8.9349	0.5567	H_0 rejected	There is spatial autocorrelation
X_4	9.1621	0.5694	H_0 rejected	There is spatial autocorrelation
X_5	5.9853	0.3456	H_0 rejected	There is spatial autocorrelation
Sisaan	4.9735	0.3029	H_0 rejected	There is spatial autocorrelation

Based on the Moran Index test using a significance level of $\alpha = 0.05$, the value $Z_{\alpha/2} = Z_{0.025} = 1.96$ is obtained. In the Moran Index test using the Rook Contiguity weighting value $Z(I)$ on the independent variable and the dependent variable has a value greater than $Z_{\alpha/2} = 1.96$. From the results of this decision it can be said that H_0 is rejected, which means that there is a spatial autocorrelation for each independent variable and the dependent variable with Moran's Index value in the range $0 \leq I < 1$ indicating a positive spatial autocorrelation. In the Moran Index test the grouping between Regencies/Cities can be seen using the Moran Scatterplot presented in Figure 6. as follows.

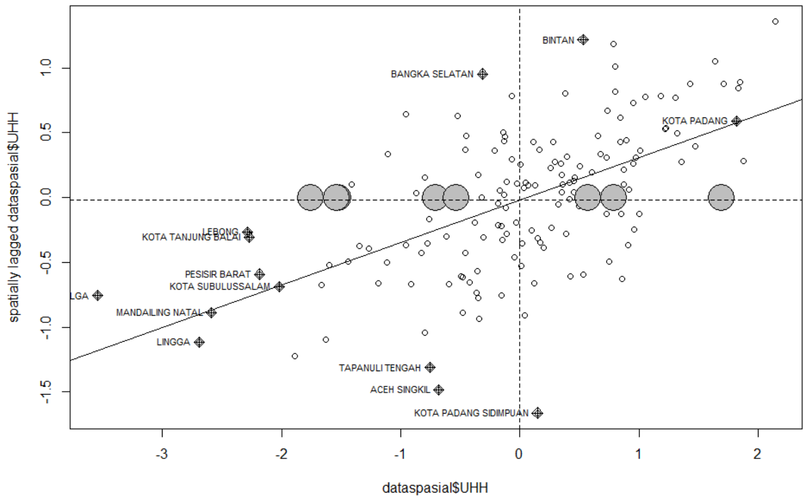

Figure 6: Moran Scatterplot Life Expectancy

Based on Figure 6 it shows that the data pattern is in quadrant I and quadrant III. Regencies/cities that are in quadrant I (High-high) are Bintan Regency, Padang City. This Regency/City has a high life expectancy and is close to other Regencies/Cities which have a high life expectancy as well. Meanwhile Regencies/Cities in quadrant III (Low-low) are Lebong Regency, Tanjung Balai City, West Coast District, Subulussalam City, Sibolga City, Mandailing Natal Regency, Lingga Regency, Central Tapanuli Regency, Aceh Singkil Regency. This Regency/City has a low life expectancy and is close to other Regencies/Cities which have a low life expectancy as well.

After testing the spatial autocorrelation, the next step is to perform the calculation results of the Durbin spatial model using the Queen Contiguity and Rook Contiguity weighting matrices which can be presented as follows:

Table 5: The results of the Durbin spatial model of the Queen and Rook weighting matrices

Variable	Coefficient		*p-value*		Conclusion
	Queen	*Rook*	*Queen*	*Rook*	

Y	-0.031	-0.032	0.612	0.602	No effect
X_1	0.377	0.376	3.73×10^{-6}	4.69×10^{-6}	Influential
X_2	0.059	0.058	0.460	0.475	No effect
X_3	0.059	0.064	0.476	0.443	No effect
X_4	-0.202	-0.196	0.017	0.021	Influential
X_5	0.152	0.154	0.037	0.035	Influential
Lag.X_1	-0.242	-0.244	0.108	0.108	No effect
Lag.X_2	0.059	0.065	0.687	0.661	No effect
Lag.X_3	0.099	0.090	0.375	0.418	No effect
Lag.X_4	0.098	0.083	0.387	0.461	No effect
Lag.X_5	-0.106	-0.110	0.486	0.469	No effect
ρ	0.516	0.512	2.49×10^{-7}	3.50×10^{-7}	Influential

Based on Table 5, it shows that the durbin spatial model with the Queen Contiguity and Rook Contiguity weight matrices produces the same conclusion, namely that there are 3 influential independent variables because they have a p-value smaller than $\alpha = 0.05$. These variables are the average length of schooling (X_1), the percentage of poor people (X_4), and GRDP at current prices (X_5) which have a significant effect on life expectancy in districts/cities on the island of Sumatra. Comparison of the p-value of the significant variables, it can be seen that the p-value of the Queen Contiguity weighting is smaller than the Rook Contiguity weighting p-value.

In this study, the selection of the best model was carried out by conducting comparisons using Akaike's Information Criterion (AIC). The best model can be determined based on the smallest AIC value. The results of the comparison of AIC values for each model can be presented in Table 6 as follows:

Table 6: Comparison of the Durbin spatial model with Queen and Rook weights

Model	**AIC**
durbin spatial model with Queen weight matrix	365.22
durbin spatial model with Rook weight matrix	366.02

Based on the comparison of AIC values, it is obtained that the Durbin spatial model with the best weighting matrix is the Durbin spatial model with Queen Contiguity weights because this model has a smaller AIC value than the Durbin spatial model with Rook Contiguity weights.

4. Conclusion

Based on the results of the discussion, it can be concluded that modeling the factors that affect the life expectancy of the Regency/City population on Sumatra Island uses the Durbin spatial model analysis with the best weighting matrix being the Queen Contiguity weighting matrix because it has a smaller AIC value of 365.22. In addition, in the Durbin spatial model analysis, there are three variables that have a significant effect on the life expectancy of the population in the Regency/City of Sumatra Island in 2021, namely the average length of schooling, the percentage of poor people, and GRDP at current prices.

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