Determinants of Leprosy Prevalence in Sulawesi Island Using Spatial Error Model

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Article Info	ABSTRACT
	Leprosy is one of the infectious diseases and has become a serious health problem in Indonesia. There are still many areas in Indonesia that have not met the leprosy elimination status. One of them is Sulawesi Island. Leprosy can spread across regions. The incidence of leprosy in an area can affect the condition of leprosy in other areas. Therefore, spatial regression is used to analyze the determinants of leprosy prevalence in Sulawesi Island. This study used data from Health Profile and Province in Figure publications with an analysis unit consisting of 81 districts in Sulawesi Island. The results show a spatial effect on leprosy prevalence exists in Sulawesi Island. Queen contiguity-based spatial weights are also considered while performing the spatial analysis. Using Spatial Error Models, the results show that population density, the number of multibacillary (MB) leprosy cases, and spatial effect significantly affect the leprosy prevalence. In contrast, a clean and healthy lifestyle, proper water access, and proper sanitation access do not significantly affect the leprosy prevalence. Because the spatial effect on the leprosy prevalence exists between districts in Sulawesi Island, so each local government should collaborate to reduce the prevalence of leprosy.

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A. INTRODUCTION

This Leprosy is an infectious disease and a serious health problem because of the disability it can cause. According to the *World Report on Disability* from World Health Organization (WHO), leprosy is one of the main causes of disability. It can be transmitted through respiration or contact with the patient. This causes leprosy to spread easily and generally occurs in developing countries, including Indonesia. The number of leprosy cases in Indonesia is also still fluctuating every year. Based on *Profil Kesehatan Indonesia*, the number of leprosy cases in Indonesia from 2013 to 2017 is still fluctuating, peaking at 17.202 cases in 2015. Meanwhile, in 2017 the number of leprosy cases in Indonesia has decreased significantly compared to previous years. However, based on data from WHO, Indonesia is the third country with the most leprosy case in the world, contributing roughly about 7.72% of all leprosy cases in 2017. In addition, based on the publication *Profil Kesehatan Indonesia* in 2017, cases of leprosy patients with level 2 disability is 4.26 per 1,000,000 population (Kemenkes RI, 2017). Some cases and relatively high disability shows that leprosy eradication in Indonesia has not been fully achieved. Therefore it is necessary to provide a counter-measures to help eliminate leprosy cases in Indonesia.

Indonesia has achieved the status of leprosy elimination. Elimination of leprosy in *Profil Kesehatan Indonesia* and WHO is defined as an area with a leprosy prevalence < 1 per 10,000 population. However, on a smaller scale, many areas have not reached leprosy elimination status, including Sulawesi Island. In 2017, the condition of leprosy prevalence on Sulawesi Island was still quite high. None of the regions on the Sulawesi Island have achieved the leprosy elimination target. The highest leprosy prevalence is

in North Sulawesi (leprosy prevalence: 2.04), and the lowest is in Central Sulawesi (leprosy prevalence: 1.1). In addition, the total cases of leprosy in Sulawesi Island, which reached 2,633 people, contributed about 16.5% of the total cases in Indonesia (Kemenkes RI, 2017). These findings show that the condition of leprosy on Sulawesi Island needs attention and studied further.

The incidence of leprosy in one area can spread to other surrounding areas. This is supported by the nature of leprosy, which is an infectious disease and can occur across regions. This situation also needs attention because there are indications that the incidence of leprosy in an area can affect the condition of leprosy in other areas. Therefore, spatial regression, particularly spatial error model was used to analyze the leprosy prevalence in areas of Sulawesi Island because it is considered capable of determining the factors that affect the leprosy prevalence, as well as taking into account the appropriate spatial effects that match the analysis units in this study.

Many studies research leprosy, but only a few focus on eastern Indonesia, such as Sulawesi. Using Spatial Durbin Model (SDM), (Ernawati et al., 2016) find that percentage of households that practice a clean and healthy lifestyle, population density, percentage of poor population, and percentage of public health centers per 100,000 population significantly affected leprosy prevalence in East Java. (Shovalina and Atok, 2016) use Geographically Weighted Regression (GWR) and found that every district have different significant variables, including the percentage of households that have non-brick walls, population density, poor population percentage, and the percentage of households that practice a clean and healthy lifestyle. (Emerson et al., 2020) also researched leprosy in 2020 by conducting a case-control study in North Gondar, Ethiopia. It is found that the Water, Sanitation, and Hygiene (WASH) factor that was significantly associated with leprosy is open sewage, absence of access to soap, access to water, hand washing practices, and water sources. Spatial analysis also has been conducted by (Pratiwi et al., 2020) and (Pratiwi et al., 2018). Using spatial econometric and spatial Durbin model, each research models economic growth, poverty, and unemployment.

The studies conducted by (Dzikrina and Purnami, 2013); (Ernawati et al., 2016); and (Prakoeswa et al., 2020) used a spatial analysis approach to study the effect of regional aspects on cases of leprosy. However, among studies on leprosy, the focus of research on the Sulawesi Island area has never been generated before. Based on the problem, it is necessary to study determinants of the leprosy prevalence on Sulawesi Island. Because leprosy is an infectious disease that can occur across regions, the analysis also needs to be studied spatially to determine if spatial aspects affect leprosy in Sulawesi Island in 2017. This study specifically uses the social condition variables that indicate as determinants of leprosy prevalence in Sulawesi Island, such as population density, the number of multibacillary (MB) leprosy cases, a clean and healthy lifestyle, proper water access, and proper sanitation access. Among similar studies on leprosy, the focus of research on the Sulawesi Island area has never been generated before.

Based on the problem, it is necessary to study determinants of the leprosy prevalence on Sulawesi Island in 2017. The main objective in this study is to find the factors that affecting the leprosy prevalence, while also finding the spatial effect on leprosy prevalence. Because leprosy is an infectious disease that can occur across regions, the analysis also needs to be studied spatially to determine if spatial aspects affect leprosy on Sulawesi Island in 2017.

B. LITERATURE REVIEW

This research uses cross-section spatial data which is used by (Bivand et al., 2021) and be written as follows:

$$\boldsymbol{y} = \rho \boldsymbol{W} y + \boldsymbol{X}\boldsymbol{\beta} + u \tag{1}$$

with:

$$\boldsymbol{u} = \lambda \boldsymbol{W} u + \boldsymbol{\varepsilon} \tag{2}$$
$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2 I) \tag{3}$$

with:

$\boldsymbol{y}$	=	vector of response variable
$\boldsymbol{X}$	=	matrix of predictor variable
$\boldsymbol{\beta}$	=	regression coefficient
ρ	=	parameter coefficient of Spatial Lag
λ	=	parameter coefficient of Spatial Error
$\boldsymbol{u}$	=	error vector of standard model
$\boldsymbol{\varepsilon}$	=	error vector of Spatial Error model
$\boldsymbol{W}$	=	spatial weighting matrix

There are several possible models that can be formed from the General Spatial Model in Equations 1-3, including:

1. If $\rho = 0$ and $\lambda = 0$

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

The model in Equation 4 is known as the classical regression model or commonly referred to as the Ordinary Least Square (OLS) regression model. OLS regression has no spatial effect in it.

2. If $\rho \neq 0$ and $\lambda = 0$

$$\boldsymbol{y} = \rho\boldsymbol{W}y + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{5}$$

The equation is referred to Spatial Lag Model or Spatial Auto-Regressive Model (SAR). This model assumes a spatial lag effect on the dependent variable between regions, but no spatial effect on the error.

3. If $\rho = 0$ and $\lambda \neq 0$

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \lambda\boldsymbol{W}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{6}$$

This equation is the Spatial Error Model (SEM) regression. In this equation, the effect of spatial lag on the dependent variable does not exist, but there is a spatial effect in the error between one region and another.

1. Moran's Error Test

Moran's I statistic (error) was developed to capture the spatial dependencies between observations. Moran's I statistics (error) is used as an index to identify the distribution of observations in each location, whether clustered, random, or uniform (dispersion) pattern. The null hypothesis is there is no spatial dependency in error ($I_e = 0$), and the statistic test:

$$Z_{\text{score}} = \frac{I_e - E(I_e)}{\sqrt{var(I_e)}} \sim N(0,1) \tag{7}$$

$$I_e = \frac{\boldsymbol{\varepsilon}'\boldsymbol{W}\boldsymbol{\varepsilon}}{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}} \tag{8}$$

$$E(I_e) = \frac{tr(\boldsymbol{MW})}{n-k} \tag{9}$$

$$Var(I_e) = \frac{tr(\boldsymbol{MWMW'}) + tr(\boldsymbol{MWMW}) + [tr(\boldsymbol{MW})]^2}{(n-k)(n-K+2)} - [E(I_e)]^2 \tag{10}$$

$$\boldsymbol{M} = \boldsymbol{I} - \boldsymbol{X}(\boldsymbol{X'X})^{-1}\boldsymbol{X'} \tag{11}$$

where:
- $\boldsymbol{M}$ = projection matrix
- n = number of observations
- k = number of parameters
- $\boldsymbol{W}$ = spatial weighting matrix

The null hypothesis is rejected when $|Z_{\text{score}}| > Z_{\frac{a}{2}}$ or $p - value < \alpha$.

2. Lagrange Multiplier Test (LM Test)

Lagrange Multiplier (LM) test is used to test spatial dependencies. LM Test performs tests on the lag coefficient and spatial error, which aims to determine the right model to be used in spatial regression analysis. The null hypothesis of LM test for the lag coefficient is no spatial lag effect on the dependent variable, and the statistic test:

$$LM_\rho = \frac{\left[\dfrac{\boldsymbol{\varepsilon}'\boldsymbol{WY}}{\sigma^2}\right]^2}{\dfrac{\boldsymbol{B}}{\sigma^2}} \sim \chi^2_{(1)} \tag{12}$$

$$B = \left[(\boldsymbol{W} \times \boldsymbol{\beta})'M(\boldsymbol{W} \times \boldsymbol{\beta}) + \boldsymbol{T}\sigma^2\right] \tag{13}$$

$$\boldsymbol{T} = tr[(\boldsymbol{W'} + \boldsymbol{W})\boldsymbol{W}] \tag{14}$$

where:

B = projection matrix

T = trace matrix

λ = parameter coefficient of $Spatial\ Error$

σ^2 = variance of regression model

While the null hypothesis of LM test for error is no spatial in error, and the statistic test:

$$LM_\lambda = \frac{\left[\frac{\boldsymbol{\varepsilon}'\boldsymbol{W\varepsilon}}{\sigma^2}\right]^2}{\boldsymbol{T}} \sim \chi^2_{(1)} \tag{15}$$

Both tests follow the Chi-Square distribution with a degree of freedom of one. If the LM statistic is greater than the critical value of Chi-Square, then H_0 is rejected.

3. Spatial Autoregressive Model (SAR)

According to (Ver Hoef et al., 2018), to test the significance of the spatial lag coefficient (ρ), the Likelihood Ratio Test (LRT) is used. The null hypothesis is spatial lag coefficient is not significant, with with a statistical test:

$$LR = \left\{ -2\ln|\boldsymbol{I} - \rho\boldsymbol{W}| + \frac{1}{\sigma^2}[(\boldsymbol{I} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{X\beta}]^T[(\boldsymbol{I} - \rho\boldsymbol{W})\boldsymbol{y} - \boldsymbol{X\beta}] - \frac{1}{\sigma^2}[\boldsymbol{y} - \boldsymbol{X\beta}]^T[\boldsymbol{y} - \boldsymbol{X\beta}] \right\} \tag{16}$$

The null hypothesis is rejected if the LR value is greater than $\chi^2_{1-\alpha(1)}$.

4. Spatial Error Model (SEM)

The Likelihood Ratio Test is used to check for spatial dependencies in error. The null hypothesis is spatial Error coefficient is not significant, with a statistical test:

$$\begin{aligned} LR = -2 \Big\{ &-\frac{n}{2}\ln\sigma^2 - \frac{1}{2}\ln\left|(\boldsymbol{I} - \boldsymbol{\beta})^{-1}(\boldsymbol{I} - \boldsymbol{\beta})^T\right| - \frac{1}{2\sigma^2}(\boldsymbol{y} - \boldsymbol{X\beta})^T\left[(\boldsymbol{I} - \boldsymbol{\beta})^{-1}(\boldsymbol{I} - \boldsymbol{\beta})^T\right]^{-1}(\boldsymbol{y} - \boldsymbol{X\beta}) \\ &+\frac{n}{2}\ln\sigma^2 + \frac{1}{2\sigma^2}(\boldsymbol{y} - \boldsymbol{X\beta})^T(\boldsymbol{y} - \boldsymbol{X\beta}) \Big\} \end{aligned} \tag{17}$$

The null hypothesis is rejected if the LR value is greater than $\chi^2_{1-\alpha(1)}$.

5. Wald test

Wald test is used to test the significant effect of each independent variable in the spatial model. The null hypothesis is k-th independent variable has no significant effect on the dependent variable, with statistic test:

$$Wald = \left(\frac{\widehat{\beta}_k}{se(\widehat{\beta}_k)}\right)^2 \sim \chi^2_1 \tag{18}$$

Null Hypoheses is rejected if Wald $> \chi^2_{\alpha,1}$

C. RESEARCH METHOD

This study examines the leprosy prevalence on Sulawesi Island in 2017. The analysis units of this study are all districts in Sulawesi Island, which consists of 81 districts. The study uses secondary data from the publication of Health Profiles of each province on Sulawesi Island in 2017, as well as the publication of Provinces in Figures of each province on Sulawesi Island in 2018. The dependent variable is the leprosy prevalence in each district. The independent variables are population density ("Dense"), the percentage of household who practice clean and healthy lifestyle ("PHBS"), the percentage of household who has good sanitation ("Sanitation)" , the percentage of household who access safe water ("Water)" , and the number of MB leprosy ("LepraMB"). These variables were formulated based on previous studies about leprosy.

This study uses spatial analysis with the analytical steps carried out are as follows:

1. *Generating multiple linear regression model*

   After estimating the parameters, classical assumptions are tested. The classical assumption tests that must be fulfilled:

   (a) Normality error

   This test is carried out using the Kolmogorov-Smirnov statistic test. Errors are normally distributed when the Kolmogorov-Smirnov statistics is greater than the value of the Kolmogorov Smirnov table or when the $p - value > 0.05$.

   (b) Non-multicollinearity of independent variables

   Multicollinearity means a high relationship (correlation) between independent variables in the regression. One way to find out the existence of multicollinearity is to check the value of Variance Inflation Factor (VIF_k). If there is an independent variable that has a value of $VIF_k > 10$, then it indicates the existence of multicollinearity.

   (c) Homoscedasticity

   The assumption of homoscedasticity can be tested using the Breusch-Pagan statistical test. When the Breusch-Pagan value is greater than the Chi-Square table value (χ^2) or when value $p - value < 0.05$, then the assumption is violated.

2. Identification of spatial autocorrelation

   This is carried out to identify whether the data has spatial autocorrelation. This test uses Moran's I to test globally and Moran's Scatterplot to test locally as written in Equation 7.

3. Spatial dependency diagnosis

   This is carried out to determine the spatial regression model. The test statistic used is the Lagrange Multiplier for both LM-error and LM-lag as written in Equations 12 and 15.

4. Likelihood Ratio (LR) test

   This is performed to decide if the spatial regression model formed more suitable than the multiple linear regression modelthe decision to reject H_0 when $p - value < 0.05$.

5. Constructing the spatial regression model. Formed as follows:

$$y_i = \rho \sum_{j=1,i \neq j}^{n} w_{ij}y_j + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \lambda \sum_{j=1,i \neq j}^{n} w_{ij}u_j + \varepsilon_i \tag{19}$$

6. Conducting a Wald test

   Carried out to determine which independent variables significantly affect the dependent variable. When the $p - value < 0.05$, H_0 is rejected, which shows that the independent variable j significantly affects leprosy prevalence.

D.   RESULTS AND DISCUSSION

1.   Overview of The Leprosy Prevalence on the Sulawesi Island

The leprosy prevalence on Sulawesi Island spans from 0 to 8.49 per 10,000 population, with an average of 1.34. The area with the highest leprosy prevalence is Siau Tagulandang Biaro Islands (8.48) in North Sulawesi, while areas with the lowest prevalence consist of 3 regions, namely Palopo City (0), Mamasa District (0), and Mamuju District (0). Figure 1 shows that most of the areas have a higher prevalence compared to both Indonesia prevalence (0.7) and leprosy elimination criteria (1.0). This condition is also in line with the publication from Kemenkes RI, where almost all provinces are high endemic for leprosy concentrated in the eastern part of Indonesia, including the island of Sulawesi (Kemenkes RI, 2018). In a study conducted by (Kansil, 2014), it was found that the people in Tagulandang Biaro District, which is the district with the highest leprosy prevalence on the island Sulawesi, have limited access to health facilities (Kansil, 2014). This results in many leprosy patients that cannot get adequate treatment and are at great risk of transmitting the disease to other people. In addition, based on the report of Dinas Kesehatan Sulawesi Selatan, it is also known that in Makassar city, high cases of leprosy occur because it is influenced by the amount of negative stigma attached to people who contracted leprosy, thus making the patients more reluctant to seek for some treatment (DinkesSulsesl, 2018). This impacts the increase of leprosy and the leprosy prevalence in these areas.
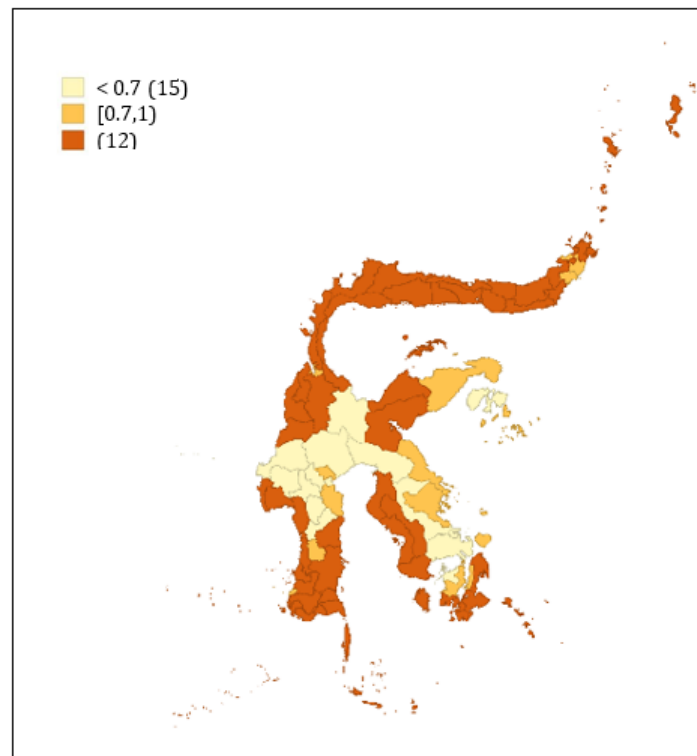
Figure 1. The leprosy prevalence per district in Sulawesi Island in 2017

2. Leprosy Prevalence Modeling with Ordinary Least Square Method

Table 2 shows the results of the partial parameter test on the linear regression model. Out of the five independent variables used, two significant variables are affecting the leprosy prevalence on Sulawesi Island in 2017, namely population density and the number of MB leprosy cases. Based on Kolmogorov-Smirnov test, the p-value is less than 0.05. This means that the error in the OLS model is not normally distributed. Abnormalities in error can be caused by several things, one of which is extreme values in a set of data that will produce a skewness distribution. This condition is also known as outliers. On the other hand, according to (Bivand et al., 2013), on a dataset that has observations in the form of islands which is an isolated area, the countermeasures that can be taken care of by creating a new subset of the data that excludes these isolated observations. Based on this basis, a test is carried out to see which data is an outlier in datasets. The test is carried out in the form of a univariate graphical test using boxplots graphs. Based on the boxplots, it is found that the outlier is observation 81, namely of the Siau Tagulandang Biaro Islands in North Sulawesi. This district has the highest leprosy prevalence in the Island of Sulawesi, which is 8.49. Also, this district is an observation with no neighboring areas. Therefore, this district will be excluded from the dataset. After outliers are removed, the data is re-tested for normality assumptions, with the results showing the normality assumption is fulfilled. The next test is the homoscedasticity test using the Breusch-Pagan test. The p-value of the Breusch-Pagan statistic is 0.1492 and greater than 0.05. It means the error variance is constant. Based on the non-multicollinearity test, it is found that there is no indication of multicollinearity in the model.

3. Spatial Autocorrelation and Spatial Dependencies

The Global Moran's Index is 0.325. A positive value indicates a positive spatial autocorrelation. The p-value is less than 0.05, so it means that there is a significant spatial autocorrelation of the prevalence of leprosy.

Two models can be formed in spatial regression, namely the spatial lag model and the spatial error model. Model selection is made by testing the Lagrange Multiplier (LM).

Table 1. Summary of Lagrange Multiplier test

Test	Queen Contiguity	
	Value	$p-value$
Moran's I (error)	3.5368	0.0004
LM error	10.1980	0.0014
LM lag	1.9161	0.1663
Robust LM error	11.0350	0.0009
Robust LM lag	2.7533	0.0971
SARMA	12.9510	0.0015

Table 1 shows that the appropriate spatial modeling in this study is the spatial error model. It is because the LM-error test results are significant, while the LM-lag test results are not significant. It means that the value of the leprosy prevalence variable in a district is influenced by the error value of its neighboring districts. Thus, it is necessary to establish a spatial error model. Queen contiguity is used in this model while considering the geographical conditions of regencies/cities on Sulawesi Island, which have many intersections with the surrounding area. It is also chosen based on a preliminary test comparing Morans Index of Queen and Rook contiguity. The Queen contiguity shows a more significant result.

4. Modeling the Leprosy Prevalence using Spatial Error Model

Based on the regression results, two variables are significant in the model, namely population density and cases of MB leprosy. In addition, the value of lambda of 0.5129 also has a p-value of less than 5% alpha. The results of this spatial error model indicate a spatial dependence on the coefficient lambda or u_i, because it is significant and has a positive sign. This means that there is a relationship between leprosy prevalence in a district with other districts, where the leprosy prevalence in a region is affected by errors from other neighboring regions

Table 2. Summary of Model Estimation

Independent Variables	Estimate	$z-value$	$p-value$
Intercept	0.851	21.314	0.03306
Density	-0.000212	-2.45239	0.01419*
PHBS	-0.000523	-0.103035	0.91793
Sanitation	0.00689	1.32023	0.18676
Water	0.000497	0.130819	0.89592
LepraMB	0.0193	54.601	0.0000*
λ	0.5129	46.905	0.0000*

$$\begin{aligned}
\text{LeproPrev}_i =& 0.8510 - 0.0002\text{Dense}_i^* - 0.0005\text{PHBS}_i + 0.0069\text{Sanitation}_i + 0.0005\text{Water}_i \\
& + 0.0193\text{LepraMB}_i^* + u_i^*
\end{aligned} \tag{20}$$

with

$$u_i = 0.5129 \sum_{i=1, i \neq j}^{n} w_i u_j$$

*significant at $\alpha = 5\%$

Based on equation 20 of the spatial error model formed, it can be interpreted that the leprosy prevalence in i-th district will decrease by 0.0002 percent when population density increases by 1, and other variables are held constant. The population density variable is significant, as in the study conducted by (Ernawati et al., 2016), where population density is also influenced by regional proximity, significantly affecting leprosy prevalence in East Java Province. This result is contrary to the research results by (Kurniawan et al., 2018), where the incidence of leprosy in Blora district is not significantly affected by population density. Meanwhile, in the research by (Shovalina and Atok, 2016), population density also significantly affects the leprosy prevalence in the Province of East Java. These findings are also similar to research by (Franco-Paredes and Rodriguez-Morales, 2016), where congested and unstructured housing can intensify the risk of leprosy transmission. A similar thing was also stated by (Setiani and Patmawati, 2015), where a large residential density will facilitate the transmission of leprosy to other people. High population

density is generally found in urban areas. A denser area means that the space for a population to move will be getting smaller. This small space of movement makes the possibility of spreading infectious diseases such as leprosy higher.

However, there is an anomaly where normally the population density should be proportionally linear with the leprosy prevalence but was inversely proportional. This case can be explained when we look at the condition between population density and leprosy prevalence in each district on the island of Sulawesi. It is known that the district with high population density is centered on big cities only, while other districts tend to have a low population density. When compared to the condition leprosy prevalence, it was found that there was a tendency for a large leprosy prevalence in areas with a lower population density than in urban a areas with a high population density. Prevalence conditions that tend to be smaller in urban areas align with the adequate health facilities network in big cities, such as in Central Sulawesi. The most widely available health services and facilities are in Palu city, which includes the health office or clinics, as well as a much larger number of individual physician practices if compared to other surrounding areas. More and adequate health facilities enable patients to undergo treatment, as well as increase the chances of the activity of finding people with leprosy to be carried out by leprosy officers at the health center, which supports these activities (DinkesSulsesl, 2017).

The leprosy prevalence in the i-th district will increase by 0.0193 when the total number of cases of leprosy type MB increases by 1 unit, and other variables are held constant. This finding is also similar to (Dzikrina and Purnami, 2013) research which reveals that the cases of leprosy multibacillary type affect the leprosy prevalence in East Java Province. (Zuhdan et al., 2017) found that living at home with non-lepromatous leprosy patients will increase the risk of developing leprosy by 9.5 times. This is also similar to the research of (Barreto et al., 2014) where the closer the relationship and family interaction with people who have leprosy, the higher the risk for leprosy to be transmitted. This also applies when the distance from where someone lives is getting smaller or is next to leprosy patients and increases the risk of contracting leprosy. In addition, if we look at the descriptive discussion, it is known that there is a tendency for people not to treat leprosy caused by several things, such as the absence of facilities and the amount of negative stigma from the community towards people with leprosy. These things make patients reluctant or ashamed to seek treatment, thus making leprosy suffered more severe, even lead to disability. The same condition is also proposed by (Sari et al., 2018), where people with leprosy tend to be embarrassed to take treatment because of the stigmatization of people with leprosy. This condition makes it easier for other people around the patients to be infected by leprosy.

The leprosy prevalence in the i-th district will increase by 0.5129 times spatial weighting if there is an increase in the average error in neighboring districts by 1 unit and other variables are considered constant. The average of other indicators that are not known or not included in the model in all regions that are considered neighbors will increase the prevalence of leprosy by 0.5129 units. A significant error coefficient indicates that there are other variables other than those used in this study which also affects the leprosy prevalence on the island of Sulawesi.

In related studies, it was found that the variable percentage of the population that performs a clean and healthy lifestyle has a significant effect on leprosy prevalence. In research conducted by (Dzikrina and Purnami, 2013), the percentage of households that perform a clean and healthy lifestyle significantly affects leprosy prevalence in East Java. In addition, based on research conducted by (Pramesti et al., 2020) in East Java, the clean and healthy lifestyle variable also affects leprosy prevalence. Meanwhile, in the research of (Prakoeswa et al., 2020), it was found that there is a relationship between a house's physical environment, waste disposal facilities, and personal hygiene, which are components of a clean and healthy lifestyle in women with leprosy in Gresik district. Research with similar results was also conducted by (Aprizal et al., 2017), where the cases of leprosy in Pekalongan District are influenced by the condition of the physical environment of the house, where bad environmental conditions make a person's risk of contracting leprosy become greater. On the other hand, based on the modeling results in this study, it is known that a clean and healthy lifestyle has no significant effect on leprosy prevalence. This condition is similar to (Pertiwi et al., 2020) research, where the percentage of households with clean and healthy lifestyles does not significantly affect the number of cases of leprosy. This is thought to be related to the clean and healthy lifestyle condition, which, although not evenly distributed, is, in general, have had a good percentage. This condition is supported by the Indonesian health performance promotion report, where the achievement of district indicators that already have clean and healthy lifestyle policies in 2017 reached 60.89%. The negative sign on the clean and healthy lifestyle coefficient also indicates that when the percentage of clean and healthy lifestyle increases, the leprosy prevalence decreases, but is not significant due to the uneven distribution of clean and healthy lifestyle achievements.

Sanitation is one of the variables that does not significantly affect leprosy prevalence. On the contrary, in a study conducted by (Sabil et al., 2018), it was found that that the percentage of the population with access to proper sanitation has a significant effect on the leprosy prevalence in South Sulawesi Province. In addition, the research conducted by (Rismawati, 2013), finds that

house sanitation has a significant effect on the incidence of multibacillary leprosy at the leprosy polyclinic of Tugurejo Hospital Semarang. This condition is also similar to the research of Emerson et al., where low sanitation is closely related to leprosy infection in the Ethiopian region (Emerson et al., 2020). This variable is not significant, allegedly influenced by the distribution of access to proper sanitation on the Sulawesi Island. The highest percentage of access to proper sanitation in Sulawesi Island is in South Sulawesi (62.84%), which is still far from the target of Rencana Pembangunan Jangka Menengah Nasional (RPJMN). Other provinces are also still below this value.

Access to proper water is a variable that has no significant effect on the leprosy prevalence on the island of Sulawesi. This result is contrary to the research done by (Prakoeswa et al., 2020), where clean water facilities correlate with the incidence of leprosy in women in Gresik District. The same thing also occurred in the study by Emerson et al., where the absence of access to clean water correlated with the incidence of leprosy in the Ethiopian region (Emerson et al., 2020). The insignificance of this variable is allegedly caused by the conditions of the percentage of access to proper water, which is not evenly distributed in all areas on the island of Sulawesi. The achievement of households with access to proper water in each province on the island of Sulawesi is still too far from the target in the RPJMN, which is 100%.

E.   CONCLUSION AND SUGGESTION

The spatial effect on the leprosy prevalence exists between districts in Sulawesi Island in 2017. This indicates that the leprosy prevalence in an area will impact the leprosy prevalence in other surrounding areas, especially by the error of the leprosy prevalence from the surrounding area. In addition, based on modeling using SEM, it is found that population density and the number of MB leprosy significantly affect the leprosy prevalence.

In dealing with leprosy, the government is expected to consider that leprosy is an infectious disease that can spread within and between regions, particularly adjacent or neighboring areas. This way, each local government should collaborate to reduce the prevalence of leprosy, so the policies. will be more sustainable and tackle leprosy. For future research, it is highly recommended to account more variation of available variables, while also considering a different method of spatial approach.

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